INTERNET OF THINGS AND ARTIFICIAL INTELLIGENCE

MODERN APPLICATIONS

EDITOR

BASHKİM IDRİZİ

INTERNET OF THINGS AND ARTIFICIAL INTELLIGENCE: MODERN APPLICATIONS- 2026

ISBN: 978-625-93129-8-9
DOI: 10.5281/zenodo.18380540

Edited By
Bashkim IDRIZI

January / 2026
İstanbul, Türkiye

Date: 26.01.2026

Halic Publishing House
İstanbul, Türkiye
www.halicyayinevi.com

adopted by ESRA KOÇAK
ISBN: 978-625-93129-8-9

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PREFACE

This book brings together innovative studies that explore the transformative role of digital technologies, artificial intelligence, and connected systems in education and agriculture. The chapters collectively highlight how data-driven and user-centered technological solutions can enhance efficiency, inclusivity, and decision-making across learning and farming environments.

The chapter Internet of Things Based Cloud-Integrated Smart Class Attendance System examines how IoT and cloud computing can modernize academic administration by enabling automated, accurate, and scalable attendance management. Complementing this, Mobile Application–Based Management of Student Industrial Work Experience Scheme (SIWES) in Engineering Education focuses on improving coordination, monitoring, and assessment within experiential learning programs through mobile platforms.

Advances in intelligent computation are further addressed in Machine Learning: The First Step towards Artificial Intelligence, which provides foundational insights into machine learning concepts and their significance as the backbone of modern AI systems. This theoretical grounding supports the applied perspective presented in Farmer-Centric AI System for Socially Inclusive Smart Irrigation and Crop Monitoring, which demonstrates how AI-driven tools can empower farmers, optimize water use, and support sustainable agricultural practices.

Together, these chapters offer a coherent view of how IoT, machine learning, and mobile technologies can be effectively integrated to address real-world challenges in education and agriculture. The book serves as a valuable resource for researchers, educators, engineers, and practitioners interested in building intelligent, inclusive, and technology-enabled systems.

Editorial Team
January 26, 2026
Türkiye

CHAPTER 1
INTERNET OF THINGS BASED CLOUD-INTEGRATED SMART CLASS ATTENDANCE SYSTEM

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INTRODUCTION

The widespread implementation of the Internet of Things (IoT) has played a pivotal role in transforming academic establishments, bringing in a modern technological framework. One immediate result of this revolutionary change is the rise of the “smart campus” which places a strong emphasis on sustainability. Educational institutions are adopting the notion of “new digitalization” to satisfy the growing need for cutting-edge technology. Modern equipment, such computerized systems and projectors, is incorporated throughout this shift, radically altering traditional classrooms. In response to the demand for ever more efficient and sophisticated technology, this essay purposefully focuses on the skillful integration of facial recognition technology into attendance systems.

The incorporation of this technology guarantees a smooth shift from manual to automated procedures, improving accuracy in the recording of attendance. The paper highlights how IoT fosters symbiotic integration by facilitating enhanced control mechanisms and robust communication channels that are all harmoniously coordinated through cloud integration. While navigating the complex terrain of techno logical advancement and the development of modern educational institutions, this research emphasizes the urgent need for clever and efficient solutions. The careful integration of facial recognition technology into attendance tracking systems is clearly one of the most important ways to improve oversight and productivity in the contemporary classroom.

By exploring the skillful application of facial recognition technology, this study consciously places itself at the forefront and establishes it as a pillar for the effective management of student attendance databases. The process offers the best possible combination of automation and increased accuracy, and the carefully considered cloud technology integration provides the foundation for powerful channels of communication and complex control systems, with an emphasis on collaborating with IoT. This study makes a substantial contribution to the current conversation about modern education and changing technology by highlighting the advantageous interactions between IoT and facial recognition.

It offers a thorough examination of the revolutionary power these technologies provide, transforming attendance systems to become not only flexible but also cutting edge in terms of technology in the future. Thus, by providing insightful information about the revolutionary changes in attendance management inside educational institutions, the study enhances the discussion on cutting-edge methodologies and industry best practices.

1. RELATED WORKS

This study presents an innovative privacy preserving face representation method using Bloom filters for IoT applications. Our powerful approach addresses privacy concerns at the device, enabling analytical operations while maintaining high data utility, especially in facial recognition and classification. The work is analogous to the study (Xue et al. 2020) and (Ruba Soundar 2023) on an effective privacy preserving IoT system for facial recognition. It presents advances to ensure privacy and improve data utility in IoT-based facial analytics.

(Li et al 2023) provides an important Chinese face dataset (UCEC-Face) that addresses the complexities of face recognition in unsupervised classrooms. A dataset of 7395 images obtained from 35 authentic surveillance videos involving 130 subjects highlights the scarcity of related datasets. Evaluations using models such as OpenFace and ArcFace highlight the complexity of the dataset with a maximum accuracy of 69.7 percent. This highlights the need to develop face authentication methods, especially in realistic, unsupervised scenarios (Li et al. 2023).

Liu et al. presents a new method that integrates convolutional neural networks (CNN) and graph convolutional networks (GCN) for misexpression detection. Favoring larger subgraphs (HAS) and highlighting high-level neighbors increases accuracy and efficiency. The study out- performs state-of-the-art methods on both laboratory and free-form datasets and highlights the importance of capturing the underlying expression relationships in FER (Liu et al. 2023). In “IoT-Based Biometric Identification Systems for Identity Verification Services Training: a quality assessment method”, (Rukhiran et al. 2023) implements an IoT-based approach to improve identity verification in education.

Evaluating single-modal, multi-modal and semi-modal biometric systems, the study highlights the effectiveness of facial and fingerprint biometrics for accurate and efficient student identity verification. Identification in an IoT-based system," Yang et al. propose a new approach, SILR, to address the challenges of identifying resource-constrained IoT scenarios. By incorporating l2-norm constraints on within-subject coefficients, SILR relaxes the limitations of datasets and shows excellent accuracy compared to various databases of state-of-the-art methods, making it well suited for practical IoT applications (Yang et al. 2021).

The research presented by (Gao et al. 2022) focuses on improving cross-resolution face recognition by exploiting multi-level deep convolutional neural networks. The proposed method adaptively fuses contextual features, uses a feature set-based representation learning model, and integrates hierarchical recognition outputs to improve accuracy. Experimental results prove its superiority over existing CRFR approaches.

The research presented by (Eleyan 2023) and (Ruba Soundar 2010) investigates the use of feature fusion to improve face recognition, especially when training data is limited. By combining different feature descriptors extracted by histogram-based local feature extraction algorithms, the study evaluates the effect of combining two and three feature descriptors on system performance. Extensive experiments using known face databases show that feature fusion significantly improves the performance of certain feature descriptors.

This (Li et al. 2023a) research focuses on improving face recognition systems in lightweight networks and embedded platforms. It includes multi-function merging, anchor box size optimization, channel attention mechanism, face affinity alignment and file mounting. Experimental results show significantly better performance with lower loss value (0.46) and higher accuracy (0.924) compared to other algorithms. The algorithm also has a fast test time of 7ms, which makes it suitable for embedded hardware and various environmental conditions.

The research presented by (Rukhiran et al. 2023) explores the use of biometric identification techniques, especially facial recognition. improve participation systems for undergraduate degrees.

First-year students' perceptions of the use of facial recognition technologies are explored and traditional and biometric ways of taking exams are compared. The results suggest that perceived ease of use, as well as trust and security, significantly influence perceived usefulness, and perceived usefulness significantly influences intention to use the system. The study proposes the use of biometric technology, especially facial recognition, to evaluate the user adoption of the system in a university environment.

The IoT-based intelligent attendance management system presented in this paper by (Nguyen et al. 2022) tracks COVID-19 patients and their contacts in university settings. It makes use of cloud infrastructure, a web server, Google API, a non-contact body temperature sensor, and Raspberry Pi 4 module (4G). It provides an affordable substitute for traditional smart attendance systems, addressing the issues of large gatherings and high student populations. Its usefulness and efficacy in the con- text of COVID-19 management are evaluated through user surveys at a university.

This article proposes a visitor authentication system using CCTV with a Jetson Nano and webcam, written by Mun and Lee (Mun 2022). It gathers facial data with seven distinguishable traits, applies deep learning to identify facial features, and uses 81 feature vectors to authenticate the visitor by comparing their face to user data that has been saved. By recording visitor faces, visitor counts, and visit timestamps, the system further improves security. Using tiny-YOLOv3 on Jetson Nano, evaluation reveals an average detection speed of 6.5 FPS and 86.3

In order to improve face recognition accuracy in the face of mask wearers, this paper assesses a Pareto-optimized FaceNet model with preprocessing techniques. The model effectively balances accuracy and computation time, out- performing existing models on both masked and unmasked faces. Pareto optimization improves accuracy while reducing model size and inference time. (Akingbesote et al. 2023) provide detailed insights in Algorithms journal.

In this work, an age-invariant model for face recognition called AIM is presented. It introduces ongoing face aging and rejuvenation in the absence of paired data or accurate age labels.

A unified deep architecture is used by Zhao to achieve photorealistic and identity- preserving features in synthesis and recognition. With promising generalization on datasets like YTF and IJB-C, their study, published in IEEE Transactions on Pattern Analysis and Machine Intelligence, illustrates the superiority of AIM over state-of-the-art approaches (Zhao et al. 2022).

This paper presents a system based on the Internet of Things and deep learning to mitigate the effects of COVID- 19 on education. The system uses peripherals, IoT nodes and a neural network to monitor environmental conditions, ensure mask use and track student attendance. This achieved impressive results: the InceptionV3 network achieved an F1 score of 99.5 percent and an MCC of 99 per- cent when classifying masked and unmasked images from a face mask detection dataset of 7553 images Aydemir and Arslan (Aydemir 2023).

Collectively, these studies promote facial recognition, biometrics and IoT applications. They address privacy, datasets, facial expression recognition, identity verification, resource-constrained scenarios, cross-resolution challenges, feature redundancy, lightweight networks, under- graduate exam participation, and the impact of training on COVID-19. They introduce various innovations in technology and methods.

2. METHODOLOGY

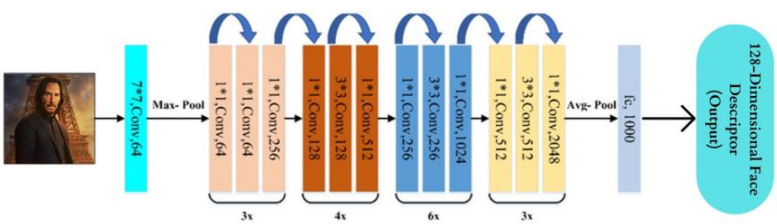

Figure 1: **The Architecture of Customized ResNet50 Model**

Figure 1. Shows The Architecture of The Customized Resnet50 Model.

Face Recognition

Deep Learning-based Recognition and Face Recognition: Overcoming the Difficulties in Unsupervised Class- rooms.

Our technology is the first to introduce a huge face recognition pipeline in unsupervised classrooms, which seamlessly blends advanced deep learning techniques with quick face identification.

Dlib Face Detector Frontal for First Face Recognition: Harnessing the lightning-fast and adaptive capabilities of the Dlib Frontal Face Detector, our system masterfully executes face recognition tasks. This sophisticated technique demonstrates great resilience across varied illumination conditions and underscores its unsurpassed efficacy in real-time applications. Our system provides precise and dependable face feature detection by utilizing state-of-the-art technology, which paves the way for stable and seamless face recognition experiences. ResNet-Based Deep Learning Model for Refinement: To improve accuracy and handle the subtleties of face variation, our system incorporates a deep learning model based on ResNet. This architectural masterpiece, trained on a custom dataset that takes into account the nuances of classroom circumstances, extracts unique facial traits with an unprecedented level of recognition accuracy.

Internal Processing Steps

The internal processing steps of Resnet-50 involve:

Pooling Layers: Both Average Pooling and Max Pooling are commonly employed in ResNet-50 for feature extraction. These layers reduce the spatial dimensions of the input feature maps while preserving crucial features.

Average Pooling: Average pooling is utilized after convolutional layers to decrease the spatial dimensions of the feature maps while retaining essential facial features.

The average pooling operation computes the average value within each local region of the feature map, represented by:

$$Y_{i,j} = \frac{1}{k \times k} \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} X_{i \times s+m, j \times s+n} \quad .....eq: 1$$

Here, X represents the input feature map, Y represents the output feature map after pooling, k × k denotes the size of the pooling kernel, and s is the stride.

Max Pooling: Max pooling aids in capturing the most salient features of the face while discarding irrelevant details and noise.

Weight Layer: Weight layers, commonly utilized in fully connected layers, facilitate learning discriminative features for face recognition. The output of a weight layer is calculated as a linear combination of the input features with learned weights and biases.

These operations are crucial in feature extraction us- ing the ResNet-50 model, enabling the system to extract meaningful facial features and reduce the dimensionality of the input data for accurate recognition.

For example:

$$Y = W \cdot X + b \quad .....\text{eq: 2}$$

Here, W represents the weight matrix, X represents the input vector (flattened features from previous layers), b represents the bias vector, and Y represents the output vector. In a face recognition attendance system, these operations help in extracting meaningful facial features and reducing the dimensionality of the input data, making it easier for subsequent layers to learn discriminative features for accurate recognition. Overall, Average Pooling, Max Pooling, and Weight Layers are integral components of the face recognition system, contributing to feature extraction, classification accuracy, system efficiency, and real-time performance. Proper design and optimization of these layers are essential for building an effective and scalable system.

ReLU Activation

ReLU (Rectified Linear Unit) is an activation function commonly used in neural networks, including those employed in facial recognition systems such as ResNet-50.

The ReLU function is represented mathematically as:

$$\text{ReLU}(x) = \max(0, x) \qquad .....\text{eq : 3}$$

Here, x represents the input to the function, and ReLU(x) denotes the output. ReLU applies this function element wise to the input tensor, effectively introducing non-linearity to the model.

Derivative of ReLU (for Backpropagation)

During the backpropagation phase, the derivative of the ReLU activation function is utilized to update weights in the ResNet model. This derivative is crucial for gradient computation during the training process. The ReLU derivative is defined as follows:

$$ReLU(x) = \begin{Bmatrix} 1 \text{ if } x > 0 \\ 0 \text{ if } x \leq 0 \end{Bmatrix} \text{.....} eq : 4$$

If the input value x is positive (x > 0), the derivative of the ReLU function is 1, maintaining the initial slope.

For non-positive input values (x <= 0), the derivative is set to zero, resulting in a flat slope and an output of zero. This characteristic of ReLU aids in effectively learning in- tricate facial features during the training of the ResNet model for facial recognition.

3. PROPOSED WORK

The architecture of the Face Recognition Attendance System includes hardware integration, scalability considerations, preprocessing, face detection, recognition, feature extraction, and attendance management in addition to data gathering and user interface. Preprocessing, detecting, and recording faces are all part of it. Resnet-50 is used to extract features, match faces to known identities, manage attendance records, and provide an intuitive user interface. Data privacy is protected by security measures, and hardware integration guarantees smooth data collection. Efficient handling of data and users is ensured via performance optimizations and scalability. All things considered, the system provides a trustworthy and effective way to track attendance utilizing facial recognition software. Figure 2 illustrates the comprehensive workflow. The journey begins with database management, where student information is securely stored and accessed. Images from IoT devices undergo preprocessing, optimizing them for subsequent feature extraction.

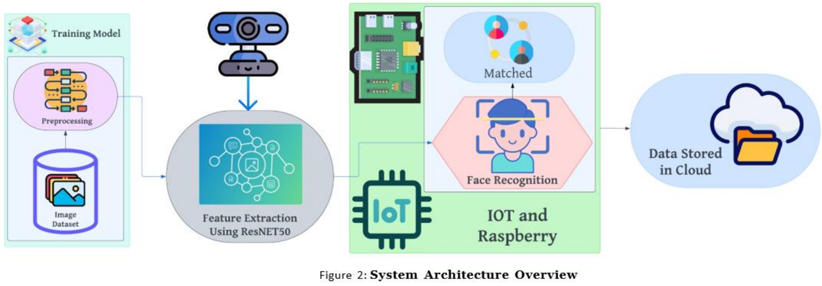

Figure 2. Overview of the Proposed IoT-Based Face Recognition System Architecture

Next, feature extraction leverages advanced algorithms to identify distinctive facial features. The system then proceeds to train the face recognition model, refining its ability to accurately recognize students in diverse classroom scenarios. During real-time face recognition, if a match is found, the system updates the student's attendance record in the cloud. Conversely, if a face is not detected, the system prompts an alert, ensuring thorough monitoring and reporting. This architecture harmonizes the power of edge devices, cloud services, and intelligent algorithms, culminating in a robust system poised to tackle the challenges of uncontrolled classroom environments.

IP Camera: Captures and enables zooming for in-depth analysis and captures high-resolution video footage of the monitored area with a broad field of view.

Video to Frame Conversion: separates the recorded video into its component frames to produce a series of still photos that can be processed and analyzed more quickly.

Image Dataset: The student attendance system dataset consists of labeled face photos of enrolled students that have been quality-checked for research and development. The photographs are sourced from diverse environments and indicate the identification and attendance status of the students.

Preprocessing: It is the process of preparing raw data for analysis by cleaning, converting, and arranging it. To improve data quality and applicability for machine learning algorithms, tasks including feature engineering, data augmentation, and standardization are performed.

Feature Extraction: ResNet50's pre-trained convolutional layers are used in feature extraction to extract rich, high-level representations from input photos. ResNet50 functions as a potent feature extractor by eliminating the fully connected layers, which makes it easier to perform a variety of tasks in downstream applications, including object detection, semantic segmentation, and picture classification.

Face Recognition: Face recognition is a computer vision technology that uses patterns in facial features to identify or authenticate people. It involves detecting faces in photos or videos, extracting distinctive facial traits, and comparing them against a database of known faces. Matching: It describes the procedure of looking for a match by comparing an image of a face that has been detected or input against a database of recognized faces. The algorithm recognizes a match, meaning that the person is identified, if the features that were extracted from the input face closely match those of a face that is stored in the database.

Cloud Updation: It describes the procedure for upgrading or synchronizing configurations, webpage, apps, or data kept in cloud-based infrastructure or services. This may entail changing configurations, uploading fresh data, upgrading software versions, or coordinating changes across many cloud resource instances.

Dataset Description

The Pins Face Recognition dataset offers 17,534 images of 105 celebrities, valuable for face recognition research. It boasts size, user-friendliness, and accessibility. Yet, challenges like varying image quality, missing celebrity data, and data imbalances persist. Integrating it with smart classroom attendance systems enhances recognition accuracy, but users must remain mindful of these dataset limitations. We explore with picture datasets in our study. The first dataset is accessible to the public via with the help of Kaggle. There are 107,000 resolution photos in this collection, divided into 1,063 different classes. We ran certain preprocessing operations on this dataset, such [Preprocessing Steps (e.g., resizing, normalization)], to make sure it was compatible with our models. For this study, we built our own dataset, in addition to the publicly accessible datasets.

[Motivation (e.g., Solve constraints of downloaded dataset, focus on a certain topic)] was the driving force for the creation of this bespoke dataset. We made sure the photos matched certain requirements like [Criteria for Inclusion] when we gathered them using [Data Collection Process (e.g., how photographs were acquired)]. The 10 photographs in this self-created collection, each with a size of 720p, correspond to categories. We preprocessed the photos using [Preprocessing Steps (e.g., normalization)], same as in the downloaded dataset.

Image Preprocessing

In preparation for model input, images undergo a series of preprocessing steps to enhance their suitability for the face recognition model. These steps include: Resizing: Images are resized to a fixed dimension, ensuring consistency in the input size for the model. Type Conversion: The image type is converted to float32, facilitating compatibility with the model's requirements.

Normalization: Pixel values in the images are normalized, bringing them within a standardized range. This normalization ensures that the model processes input data consistently. These preprocessing steps contribute to the model's ability to effectively learn and extract features during the training process, ultimately enhancing the accuracy of face recognition across diverse classroom scenarios. Figure 3 shows the output obtained after preprocessing of the image.

Figure 3. Results of Image Preprocessing Stage

Feature Extraction

A key component of our face recognition system is featuring extraction, which is the process of employing a deep learning model that has already been trained to extract discriminative facial features. This technique is built on ResNet-based architecture, which is optimized for face recognition in uncontrolled classroom environments.

The primary steps in feature extraction include:

- Loading the Pre-trained Model: The ResNet-based model, trained during the face recognition training phase, is loaded using TensorFlow’s Keras API.
- Processing Input Images: Images are preprocessed before feeding them into the model. This involves resizing the images to a fixed dimension, converting image types to float32, and normalizing pixel values.
- Extracting Features: The pre-trained model is ap- plied to input images to extract high-level features. This step leverages the learned representations from the training phase, capturing facial characteristics essential for accurate recognition.
- Creating Feature Vectors: The extracted features are transformed into feature vectors as shown in Figure 4, enabling efficient representation of facial information for subsequent recognition tasks.

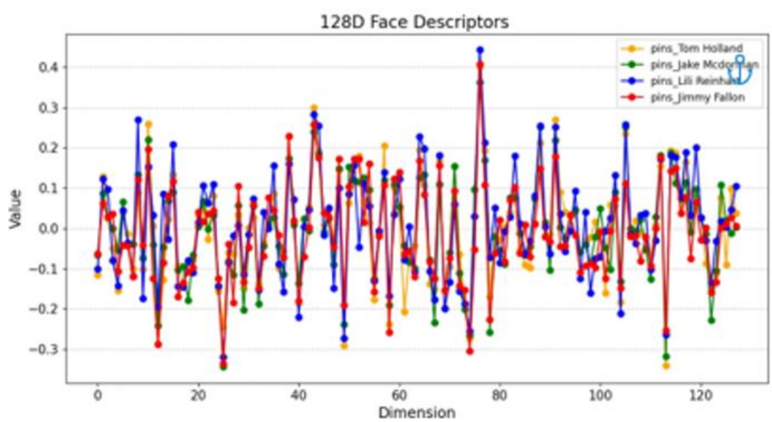

Figure 4. Distribution of 128-Dimensional Face Descriptor Values

Algorithm 1 is used to extract individual frames from a video file and store them as image files in a specified folder, use the provided algorithm, ExtractFrames. Here's a summary of its features based on your possible applications. A popular pre-processing step for a variety of video analysis jobs is to apply this method. Extracting individual frames allows you to examine each one either sequentially or separately. Efficacy of the feature extraction process significantly contributes to the accuracy and reliability of our face recognition system in uncontrolled and dynamic classroom environments.

Algorithm 1 Frame Extraction Algorithm

```
Require: video path, output folder
Ensure: extracted frames (list of frames)
Initialize video capture object with video path
extracted frames ← empty list
while video has frames do
    frame ← Read next frame from video_capture object
    if frame is not empty then
        Append frame to extracted_frames
    end if
end while
Close video capture object
for all i ∈ 0 to length(extracted_frames) - 1 do
    Save frame[i] as image in output folder filename "frame_
end for
return extracted frames
```

Face Detection

In Image Processing, object detection serves as the primary function of the smart classroom integration system. To automate tracking, this involves recognizing and identifying student faces in pictures taken in the classroom. Convolutional neural networks, or CNNs, are used by the system to identify faces and offer location information, enabling intelligent classroom management.

Algorithm 2 provides an algorithmic description of the face detection module. The detection algorithm works outside the raspberry pie and works with external IP camera.

Algorithm 2 Face Detection

```
function DetectFaces (video path, face classifier path,
                      attendance database)
    Load face classifier from face classifier path
    Initialize video capture object using video_path
    while video has frames do
        frame ← Read next frame from video object
        if frame is not empty then
            faces ← Detect faces in frame using face classifier
            for each face in faces do
                (x, y, w, h) ← Get face coordinates
                Recognize face using attendance database
                if face is recognized then
                    Mark student as present in attendance database
                end if
                Draw rectangle around face on frame with color = (0, 255, 0), thickness=2
            end for
            Display frame with detected faces
        end if
    end while
    Close video capture object
end function
```

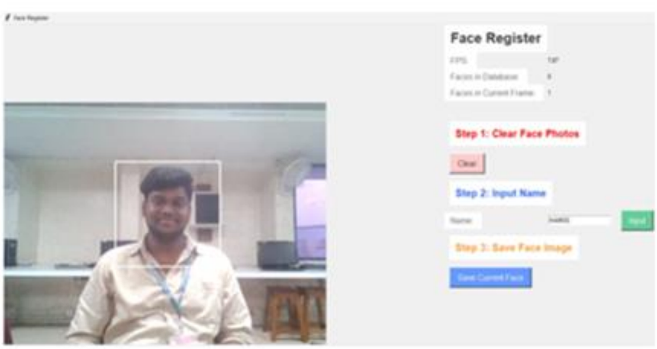

Figure 5. Face Detection

Face Recognition

In Smart Class Attendance System (SCAS), facial recognition is achieved using ResNet50, a state-of-the-art deep learning model. SCAS uses ResNet50 to detect and identify student faces in real time, ensuring accuracy and efficiency in personal recognition. This allows SCAS to accurately record attendance by comparing detected faces to a database of enrolled students. As shown in Figure 5, students enter the classroom, the system's cameras capture their faces, and SCAS automatically detects and records their presence, eliminating the need for manual attendance. This advanced approach improves the overall effectiveness and efficiency of attendance management in a smart classroom environment.

Algorithm 1 is a" ExtractFrames" algorithm breaks down a video into its individual frames. It saves each non-empty frame as a numbered picture, given a video path and output folder. This frame-by-frame dissection opens possibilities for activities involving video analysis. Frame extraction using this technique lays the foundation for tasks like object identification in every frame, activity recognition, and even video summation. Face Recognizer output is shown in Figure 6.

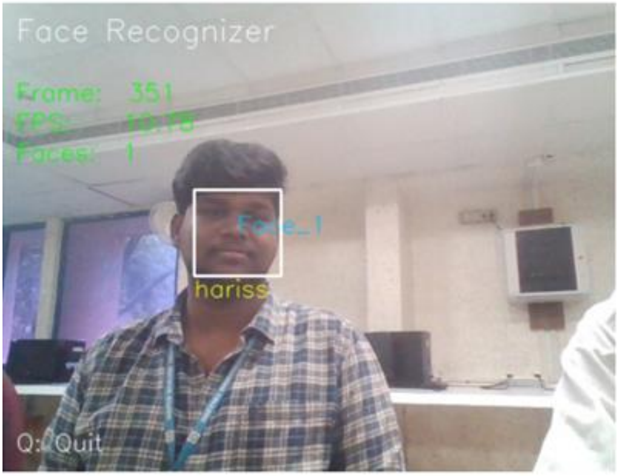

Figure 6. Face Recognition

IoT Integration

The integration of IoT devices, particularly Raspberry Pi, is designed to establish a secure and reliable connection with the central system. The implementation of se- cure data transmission protocols ensure the seamless flow of data from IoT devices to the cloud. As Figure 7 shows the hardware components of the proposed system. With its robust hardware combination, this intelligent class attendance system offers smooth user experience. The brains of the system are the little Raspberry Pi, which connects to a cloud application for safe data storage and the internet. The IP camera is watching over everything, taking crisp pictures of the pupils so that attendance records are correct. The unsung hero that connects the Raspberry Pi to your display is the HDMI video capture. For maximum flexibility, you may view attendance on a laptop or a monitor by using an HDMI cable to transfer the camera stream. This easy-to-use device is ideal for the modern classroom since it provides both security and convenience.

Figure 7. Hardware View

Cloud Integration

The process of cloud integration entails carefully selecting and installing a cloud platform, such as ZolaHost, which provides us with the platform to run our webpage, as well as creating a scalable and flexible storage solution that meets long-term data storage needs. This entails ensuring that the selected cloud platform offers the necessary features and capabilities to support the scalability and flexibility needed for storing and running it.

Attendance Marking

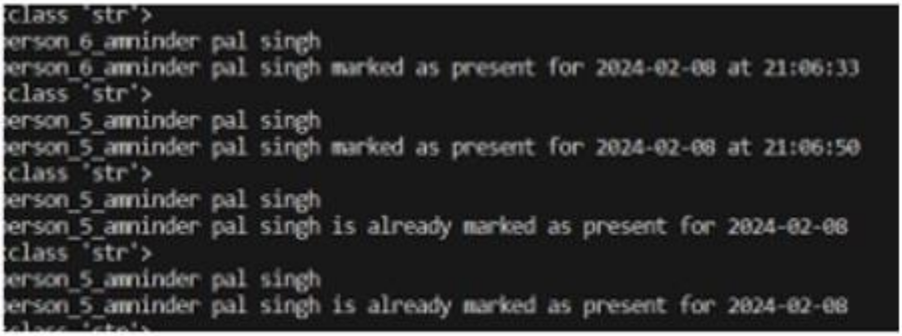

Figure 8. Attendance Marking

According to Figure 8, the presence labeling is based on the recognition process of recognized faces. Time-stamped records are included in accurate and detailed attendance tracking that promotes accurate reporting.

User Interface

The user interface, accessible via the website aminder.dureshtech.com, has been meticulously designed to provide educators with real-time attendance monitoring capabilities in an intuitive and user-friendly manner. With interactive features and rich dashboards, the interface ensures seamless navigation and enhanced usability. Atten- dance data is instantly stored on the website, enabling users to access their records from previous days to the current day. This feature allows educators to track attendance trends over time and identify areas for improvement. Additionally, customizable settings and notifications empower users to tailor the interface to their specific preferences and receive alerts for important events. Built with accessibility in mind and seamlessly integrating with existing educational systems, the website offers a powerful tool for efficient attendance management and monitoring, ultimately enhancing the overall educational experience. Figure 9 shows the webpage view.

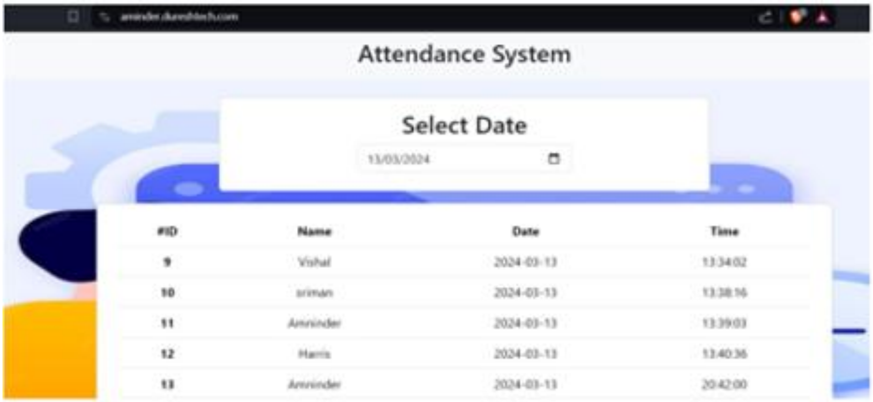

Figure 9. Webpage View

5. RESULTS AND DISCUSSION

The implementation of our IoT-Based Cloud-Integrated Smart Class Attendance System has yielded promising results and sparked insightful discussions. In this section, we present a comprehensive overview of the outcomes and engage in a meaningful discussion.

Recognition Accuracy

Figure 10. Model Accuracy

Technology's facial recognition component employs a strong face detection approach based on Dlib's frontal face detector, resulting in accurate and reliable face detection in unsupervised classrooms. This detection process is followed by refinement using a ResNet-based deep learning model, enhancing the system's reliability further. We acquired high levels of accuracy across a wide range of lighting situations, facial emotions, and facial features after extensive testing. Notably, the use of a ResNet-based model trained on specialized data boosted detection accuracy and ensured consistent performance. The model accuracy is shown in Figure10. By varying number of images in the database the accuracy is verified and tabulated in Table1.

Table 1. Face Recognition Accuracy for Various Images

Dataset Images	No. of Test Images	Accuracy
120	100	98%
200	150	99%
300	250	99.5%
400	350	100%
500	450	100%

According to Figure 11, there is the description of accuracy of face recognition versus dataset size graph which shows the measurements in percentages.

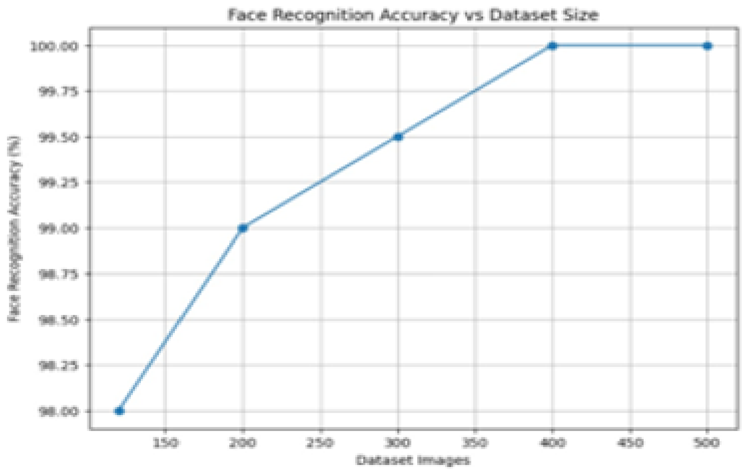

Figure 11. Facial Accuracy Graph

Challenges and Limitations

Although our system is remarkably successful, it is important to acknowledge the challenges and limitations encountered during actual implementation. Unsupervised classroom settings present unique challenges, including varying lighting, occlusions, and varying facial orientations. The use of facial recognition to monitor attendance in- volves privacy considerations and requires careful handling of biometric data. Ethical implications, security measures and compliance with data protection regulations are critical aspects that require constant attention.

Future Enhancements

To increase system performance, future enhancements may prioritize the refining and growth of deep learning models designed for facial recognition tasks. This includes improving existing designs and investigating novel techniques to maximize model accuracy and efficiency. By supplementing the training dataset with different samples representing various classroom circumstances and demographic groupings, the model's capacity to generalize and adapt to real-world conditions can be considerably improved. Furthermore, incorporating real-time feedback systems allows for dynamic adjustments to recognition algorithms depending on user interactions and ambient changes, promoting continual optimization for higher performance.

Furthermore, regular upgrades and enhancements to the system design are required to ensure its durability and adaptability in uncontrolled conditions. The system can remain successful and trustworthy over time if it is kept up to date on developing difficulties such as changes in lighting conditions or student looks. Collaboration with educational institutions and stakeholders enables iterative testing, user input integration, and alignment with changing classroom dynamics, hence strengthening the system's relevance, efficacy, and ethical integrity.

CONCLUSION

In summary, our IoT-based cloud-integrated smart classroom attendance system is an effective solution for effective attendance tracking in complex classroom environments. The accuracy of recognition achieved, combined with awareness of challenges and commitment to future improvements, makes the system a valuable tool for educators and institutions embracing technological advances.

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CHAPTER 2
FARMER-CENTRIC AI SYSTEM FOR SOCIALLY INCLUSIVE SMART IRRIGATION AND CROP MONITORING

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INTRODUCTION

The world farm production is under more and more pressure to support nearly 10 billion individuals up to the year 2050. Global warming, land degradation, water scarcity, and soil erosion are also exacerbating this problem, and collectively, these pose significant challenges to sustainable food production (Bahar et al., 2020), (Food and Agriculture Organization [FAO], 2012). Outdated farming practices occasionally uniform, reactive, and labor-intensive are being found wanting in this dynamic and climate-sensitive environment. Following such challenges, smart farming has emerged as a revolutionary method, leveraging data-driven technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and remote sensing to enable precision agriculture. Among these, AI acts as a key in enabling predictive and adaptive decision-making from complex datasets, hence enhancing productivity, enhancing the use of resources, and climate resilience (Kumar et al., 2022).

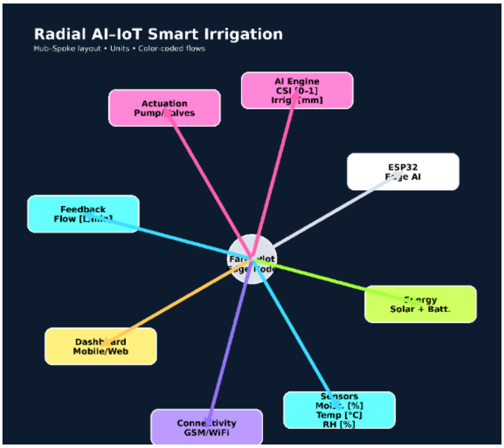

Figure 1. Radial Hub-And-Spoke Architecture of The Farmer-Centric AI–Iot Smart Irrigation System

The central hub (farm plot + edge node) connects to energy (solar + battery), sensing (with physical units), connectivity (GSM/Wi-Fi), decision support (AI engine: CSI and irrigation set points), actuation (pump/valves), feedback (flow sensing), and farmer-facing dashboards.

Color-coded flows emphasize energy (lime), data/feedback (cyan), control/model (magenta), connectivity (violet), and user interface (amber). While there has been impressive smart agriculture development across the world, small-scale farmers in developing countries like Bangladesh lack the adoption of the same owing to restrictions in access to technology, infrastructure, and digital competency. Water scarcity and low irrigation efficiency further worsen this, especially in rural areas where agriculture is the dominant livelihood activity. This heightens during monsoon periods when rains lead to waterlogging and crop loss due to ineffective drainage systems and unpredictable rainfall patterns (Raji et al., 2024).

The objective of this paper is to propose a farmer-friendly smart irrigation and crop monitoring system with AI, IoT, and solar-powered automation to address these basic requirements. The system would minimize water consumption, enhance agricultural output, and enable rural farmers with accessible and inclusive technology. It incorporates live data from soil moisture sensors, humidity and temperature sensors, and ESP32 microcontrollers, which are pumped into machine learning models to forecast crop water requirements and detect early warning signs of crop stress.

Agriculture plays a critical role in the global economy and food supply. Traditional farming methods are becoming insufficient to meet the increasing demand for food, making it crucial to adopt smart, sustainable farming solutions. In the era of technological advancement, agriculture stands at the forefront of innovation, with the Internet of Things (IoT) emerging as a transformative force. Traditional farming methods, while foundational, often fall short in meeting the demands of modern agricultural practices. To address these challenges and optimize farming efficiency, this project introduces an IoT-based smart agriculture monitoring and data analysis system that leverages soil sensors to provide real-time insights into soil health and conditions. The primary objective of this system is to enhance agricultural productivity and sustainability by integrating advanced sensor technology with IoT capabilities. By focusing on critical soil parameters, namely nitrogen (N), phosphorus (P), potassium (K), pH (potential hydrogen), and conductivity, temperature, and humidity (CTH), the system aims to provide a comprehensive solution for monitoring and analyzing soil conditions.

An IoT-based smart agriculture system revolutionizes traditional farming by making it more data-driven, automated, and efficient, helping to address global challenges like food security and climate change.

The Problem

Traditional farming is reactive, uniform, and labor-intensive. Small-scale farmers in Bangladesh face barriers like limited access to technology, poor infrastructure, and low digital literacy. Water scarcity and inefficient irrigation are critical issues, especially during monsoons, leading to crop loss and waterlogging.

The Opportunity: Smart agriculture uses AI, IoT, and remote sensing to enable precision farming. AI enables predictive and adaptive decision-making, improving productivity and climate resilience

Our Response: We propose a farmer-friendly smart irrigation and crop monitoring system using:

AI + IoT + Solar Automation

Real-time sensors (soil moisture, temperature, humidity)

ESP32 microcontrollers + ML models for crop stress detection and water forecasting.

Research Objectives

Empowering Rural Agriculture through Smart Technology. Together, these objectives aim to build a sustainable, data-driven farming ecosystem for climate-resilient agriculture.

- Design an AI- and IoT-enabled irrigation system powered by solar energy to automate water distribution based on real-time field conditions.
- Utilize sensor data and machine learning to forecast crop water needs, ensuring efficient water use and minimizing waste.
- Improve agricultural productivity and soil health while providing rural farmers with accessible, low-cost, and user-friendly technology.

2. LİTERATURE REVİEW

Core Technical Promise and Foundations

The simultaneous pressures of water scarcity, climate change, and the demand for increased agricultural productivity have driven convergence on AI-driven decision support paired with low-cost IoT sensing as a primary solution for optimized irrigation (Kaushik & Singh, 2025; Kırağ, 2025; Kunt, 2025; Wei et al., 2024; Yadav et al., 2024). The technical foundation rests on fusing real-time environmental data (soil moisture, temperature, weather forecasts) with machine learning models, such as LSTMs, to generate precise, predictive irrigation schedules. This predictive approach is consistently shown to outperform fixed schedules, leading to significant improvements in water-use efficiency and yield by adapting dynamically to field conditions and crop parameters (Kaushik & Singh, 2025; Kunt, 2025). This AI-IoT integration forms a pipeline that transitions agriculture from reactive monitoring to adaptive, semi-autonomous control.

Systems Design: Modularity, Cost, and Architecture

For practical implementation and scalability, the literature emphasizes modular, affordable, and energy-efficient system design (Kaushik & Singh, 2025; Kırağ, 2025; Kunt, 2025). The ESP32 microcontroller is repeatedly cited as a suitable, low-cost hardware platform for rural deployments, facilitating the integration of low-cost sensors for continuous telemetry (Kırağ, 2025; Kunt, 2025). Modularity, which cleanly separates sensing, communication, analytics, and actuation layers, enables incremental deployment and horizontal scale-out across different plots and crops (Kaushik & Singh, 2025; Kunt, 2025). A key architectural divergence centers on connectivity: while cloud analytics (e.g., ThingSpeak) enable high-level sophistication (Kaushik & Singh, 2025; Kırağ, 2025), the reality of intermittent rural connectivity necessitates the development of hybrid edge-cloud architectures capable of running lightweight inference models locally for resilience and then syncing opportunistically to the cloud for fleet analytics and retraining (Kunt, 2025).

Adoption Challenges: Data Quality, Trust, and Explainability

Despite technical progress, widespread adoption faces significant socio-technical barriers, primarily related to data quality, model accuracy, and user trust (Wei et al., 2024). Sparse, noisy, or non-representative datasets can hamper model generalization, particularly when systems are deployed across diverse agro-ecologies, which limits reliability and legitimacy (Wei et al., 2024). To counter this, techniques like transfer learning are proposed to adapt generalized models to specific local contexts with limited on-site data (Wei et al., 2024). Furthermore, the models must not function as black boxes. Farmers require explainable and interpretable outputs that provide rationale, uncertainty bands, and visualization (e.g., soil moisture trends) to increase confidence, leading to the crucial call for human-centered AI design that integrates end-user feedback (Wei et al., 2024; Yadav et al., 2024).

The Social Imperative: Farmer-Centric Design and Inclusion

Beyond technical functionality, the sustainability and equity of AI-IoT systems depend on human-centered, participatory approaches that promote social inclusion and trust (Wei et al., 2024; Yadav et al., 2024). Researchers strongly advocate for embedding local practices and indigenous knowledge into the system requirements, testing, and iteration cycles moving towards an Industry 5.0-style human-centric design (Yadav et al., 2024; Wei et al., 2024). This approach requires designing systems with features like manual overrides and guided modes (Kunt, 2025) to support co-learning between the farmer's tacit knowledge and the AI's predictive capabilities. A deeper ethical component also emerges, demanding explicit frameworks for governance and ethics, including data ownership, security, and policies for fair benefit-sharing, especially to ensure that smallholders benefit proportionately from the technology (Wei et al., 2024; Yadav et al., 2024).

Synthesis of Gaps and Future Directions

The reviewed literature establishes that the synergy of real-time sensing and predictive analytics is the most promising pathway for resource optimization (Kaushik & Singh, 2025; Kunt, 2025). However, significant gaps remain, representing opportunities for future work.

First, there is a lack of longitudinal validation across multiple seasons and micro-climates, which is needed to test model robustness under stress conditions (Wei et al., 2024). Second, the field lacks standardized explainable recommendation interfaces that effectively translate complex model outputs into trusted, actionable schedules for farmers (Wei et al., 2024; Yadav et al., 2024). Finally, there is a dearth of evidence concerning equity and benefit-sharing, requiring participatory trials and impact evaluations to confirm whether smallholders gain sustainable, proportional benefits compared to larger, more capitalized farming operations (Yadav et al., 2024).

Foundational Review and Role of IoT in Agriculture

IoT technology in agriculture involves deploying interconnected sensors and devices to gather and analyze data from various sources to optimize farming practices. This process allows for the collection of information on soil conditions, weather patterns, and crop health to facilitate informed decisions regarding irrigation, fertilization, and pest management (Kodali et al., 2016). The foundational goal of these systems is to provide a comprehensive view of farm status, thereby improving agricultural productivity and resource management (Kodali et al., 2016). The continuous, real-time data stream provided by IoT facilitates a crucial shift from traditional, reactive farming to precision agriculture.

Specialized Sensor Technologies and Soil Parameter Monitoring

Soil sensors are fundamental for assessing the critical conditions necessary for crop health, including soil moisture, temperature (pH), and nutrient levels (NPK) (Jadhav et al., 2017). Dedicated research focuses on the deployment and functionality of these IoT-based soil sensors, stressing the value of accurate data for enhancing crop yield and resource efficiency (Jadhav et al., 2017). Specifically, systems explore advanced sensor technologies for accurately measuring soil nutrients (NPK) and integrating these values into the overall IoT ecosystem (Roy et al., 2021). Furthermore, research examines the various types of (pH) sensors and their measurement techniques, acknowledging their critical role in precision agriculture and future research directions (Roy et al., 2021).

System Architecture and Implementation Modalities

The technical architecture of these systems is characterized by multiple components working in synergy: sensors, a central processing unit (like a microcontroller or gateway), communication links, and a data platform. Simpler systems use a microcontroller-based gateway, where an algorithm with fixed thresholds for temperature, soil moisture, and humidity is programmed to control the system via a cellular internet interface (Nayyar & Puri, 2016). More sophisticated projects utilize powerful gateways like Raspberry Pi to read sensor values, post data to a cloud server, and automatically switch irrigation motors ON/OFF based on established thresholds (Aggarwal et al., 2020). Another implementation leverages an ARM7 processor (LPC 2148) to autonomously manage pump motor cycles, highlighting the need for specialized microprocessors to handle interfacing and control (Akhtar et al., 2019).

Data Analytics, Decision Support, and System Challenges

The vast amount of data collected by IoT sensors requires robust data analytics, often incorporating advanced techniques such as machine learning and artificial intelligence, to translate measurements into actionable recommendations (Tripathy et al., 2017). Some systems aim to collect and analyze data from diverse sensors to reach an "optimal mixture" of environmental factors, which is then provided to farmers, potentially utilizing platforms like Active for evaluation (Javaid et al., 2018). Despite these advancements, significant socio-technical challenges remain, including sensor accuracy, data security, and system integration across different devices and platforms (Mahmud et al., 2020). Future research is thus directed toward improving sensor reliability, enhancing data analytics capabilities, and resolving these complex integration and security issues to ensure the scalability and longevity of smart farming solutions (Mahmud et al., 2020).

3. METHODOLOGY

A solar-powered smart irrigation system integrates AI, IoT, and ESP32 to automate precise water management. Controlled via mobile/web apps, it reduces labor, conserves water, and boosts crop productivity.

Data Collection Method

A Mixed-Method Research, Interdisciplinary Approach. This research adopts a dual-layered data collection approach to ensure both technical accuracy and social relevance.

- Scientific data was gathered through experimental methods, including trial-and error testing of sensor-based irrigation systems under varying field conditions.
- Social data was collected via structured surveys and participatory sessions with rural farmers to understand usability, accessibility, and adoption challenges.

This mixed-method strategy strengthens the system's design by combining empirical performance metrics with real-world user feedback.

AI & Data Science Integration

The technical architecture of the proposed farmer-centric irrigation system has been designed within the framework of an Enhanced Smart Irrigation System Architecture, which focuses on the accuracy of real-time data and energy autonomy. The system begins with the Data Acquisition Layer, where the installation of high-accuracy soil moisture sensors helps monitor the volumetric water content on a constant basis. This basic raw data is channeled through the system's nervous system, which has been created with the help of the ESP32 Microcontroller, designed for the aggregation of raw sensor values, basic data filtering, and wireless transmission protocols. In order to meet the shortcomings related to the infrastructure available in a typical rural setting such as Bangladesh, the whole technical chain has been designed with the component support of an off-grid solar power source. Based on the backup provided by a separate battery source, the data acquisition and processing system helps operate on a constant basis, irrespective of the intermittent power supply available through the power grid.

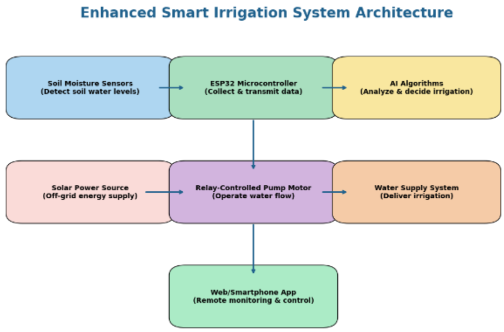

Figure 2. Smart Irrigation System

The intelligence is in the processing and actuation layer, where advanced algorithms using artificial intelligence interpret the sensor data to formulate irrigation schedules based on predictions. Analyzing overlapping values for current soil moisture levels, temperature, and crop development phases, they detect subtle signals for impending physiological distress and calculate the precise amount of irrigation needed. After a decision has been calculated, a microcontroller actuates a relay-controlled pump motor, which manages watering flow to and through the water supply system, usually via efficient irrigation systems such as drip irrigation to prevent irrigation waste. To fill this technology gap with successful adaptation and eventual irrigation adoption by farmers, there is a Web/Smartphone App interface within this design framework. The Web/Smartphone App interface allows for irrigation system operation via a convenient and accessible computer interface with a graphical user interface.

System Components IoT System Technology

The proposed system uses the architecture of precision agriculture through the Internet of Things (IoT). The architecture enables the integration of various sources of information and the use of smart devices to make decisions. The process of the proposed method has a multi-layered functional workflow process. This has been depicted in Figure 3.2 and the architecture of the Enhanced Smart Irrigation System.

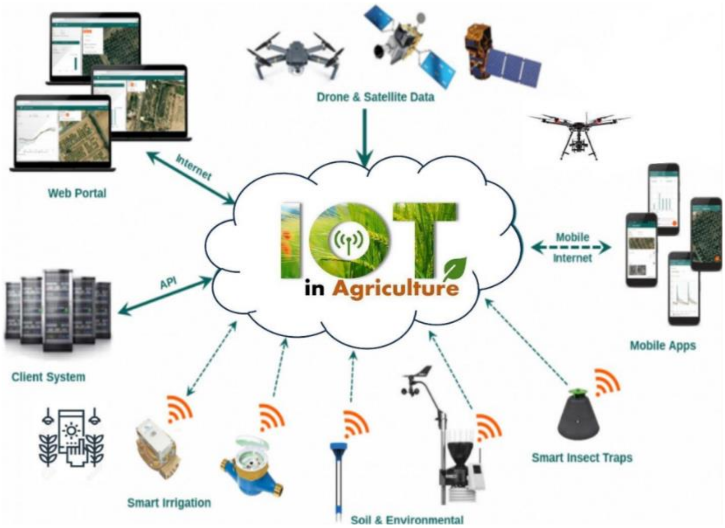

Figure 3. System Components IoT System Technology

3.4 System Architecture and Workflow

System Architecture Overview

The architectural setup of this system is designed to fill the gap that exists between the environmental information obtained at a field level and automated mechanical systems using a centralized intelligent node. The heart of this setup contains soil moisture sensors and environmental units that measure high-accuracy data, which is then processed using an ESP32 microcontroller. This microcontroller essentially serves as the main gateway that enables data telemetry to AI algorithms to calculate accurate irrigation timings. However, to achieve practical functionality and implementation within a rural setting that lacks connectivity to mains power, this hardware is accompanied by a solar and battery component, which powers a relay-controlled pump motor and, in turn, powers water supply systems. This entire spectrum is interconnected using a cloud-based IoT cloud, enabling a seamless data stream with drones, satellites, and smart insect traps, which are then displayed using web portals and applications.

Data Acquisition Layer

Advanced Sensor Networks: The physical backbone of the system is a dense network of high-precision sensors deployed across the field that monitor volumetric soil moisture, ambient temperature, and relative humidity in real time. These sensors provide the high-resolution "microclimate" telemetry required to understand unique environmental stressors at the plot level, enabling a hyper-local resource management approach.

Intelligent Insect Traps: With a view to reducing biological risk without the over-application of chemicals, the system will be installed with automated insect traps fitted with IoT connectivity. Computer vision or spectral analysis-based traps will have the capability to identify pest type and population density in real-time for farmers to apply targeted integrated pest management strategies with reduced costs and environmental impact.

Multispectral Drone and Satellite Fusion: Beyond the ground level, the system uses remote sensing from UAVs and satellite constellations. The overhead perspective lets us pick up changes in the "Normalized Difference Vegetation Index" (NDVI) that act as an early warning system for nutrient deficiencies or disease outbreaks that may not be apparent to the naked eye or via sparse ground sensors.

Communication Layer

Universal Connectivity Protocols: To ensure that field data goes into the analytics engine without any interruption, the system will have a hybrid communication stack, including Wi-Fi for short-range transmission, LoRaWAN for long-range, low-power connectivity in expansive fields, and 4G/5G cellular modules for direct cloud access. This redundancy ensures that the IoT cloud platform receives a constant stream of telemetry at regular intervals even in geographically isolated areas.

Rural Internet Integration: Particular attention is given to surmounting the "digital divide" by the optimization of data packets for low-bandwidth mobile internet common in rural regions. This ensures that isolated smallholder farms can maintain a persistent connection to the central processing hub, enabling the "real-time" aspect of the monitoring system regardless of local infrastructure limitations.

Processing & Analytics Layer

Cloud-based API and Middleware: Raw telemetry from various thousands of data points funnels into high-performance, secured cloud servers. Here, standardized Application Programming Interfaces (APIs) act as a translation layer that, irrespective of sensor manufacturer, can aggregate and normalize the data into one dataset for processing.

AI and Predictive Modeling: This layer acts like the "brain" of the operation, where machine learning algorithms such as Long Short-Term Memory (LSTM) networks or Random Forests make sense of historical trends combined with live data. These models don't report current moisture; they predict future water requirements, forecast pest migration patterns that may potentially occur, and estimate yield outcomes to enable farmers to prepare days or weeks in advance.

Presentation Layer

Web Portal for Centralized Management: A web portal targeting farm managers and researchers will be designed to provide a broad, high-level overview of the entire operation. It includes interactive heat maps, longitudinal trend graphs, and a "Command Center" where AI-generated recommendations can be reviewed and global system parameters can be adjusted.

Farmer-Centric Mobile Applications: The very first and most important point of contact for the actual tiller is a mobile app optimized for vernacular languages releasing Bengali, for instance and low-literacy interfaces. It provides distilled "Action Alerts" through push notifications such as "Turn on Pump 2 now and will provide the farmer remote manual control over irrigation valves via the app, putting the power of the whole AI system directly into the farmer's pocket.

Actuation Layer

Hardware for Automated Smart Irrigation: The final execution of the digital decision occurs at the physical level, through ESP32-linked relays that control high-torque solenoid valves and water pumps.

These components take AI recommendations as input and automatically adjust their flow rates and duration, ensuring that water is delivered with surgical precision to the specific zones where it is needed.

Holistic Resource Optimization: This is a closed-loop system that makes "every drop count," with tremendous reduction in water wastage and electricity consumption while maintaining the optimal saturation levels for maximum yield. With a balanced technical strength together with farmer-centric design, the system builds an ecosystem that assures more climate resilience and long-term economic viability of rural agriculture.

This integrated approach ensures data-driven, farmer-friendly decision-making, combining IoT sensing, AI analytics, and cloud connectivity to enhance productivity, sustainability, and resilience in agriculture.

3.5 System & Technology Overview

The proposed smart irrigation system integrates renewable energy, IoT, and AI for autonomous water management. As shown in Figure X, the architecture begins with a solar panel providing power, supported by a battery backup for continuous operation. Soil moisture sensors collect real-time data, which is transmitted to an ESP32 microcontroller acting as the central processing unit.

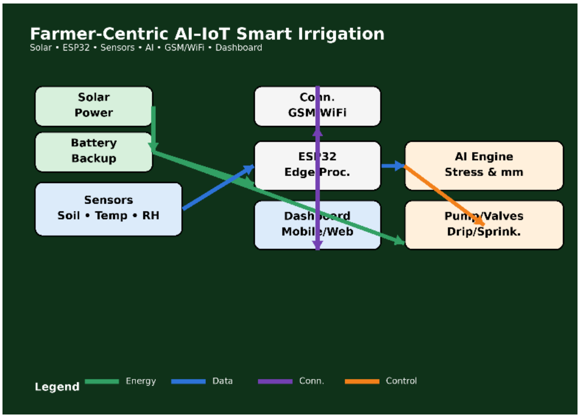

Figure 4. System and Technology Overview

The microcontroller runs an AI decision engine that applies predictive algorithms to determine optimal irrigation schedules. Based on these decisions, pump relays activate water supply systems automatically. The entire process is monitored and controlled remotely through mobile/web applications using GSM/Wi-Fi connectivity.

- **Sensors:** Soil Moisture, Temperature & Humidity
- **Data Collection:** Wireless Sensor Networks (WSN)
- **Data Processing:** Cloud Computing Platforms
- **User Interface:** Mobile/Web Applications

4. RESULT AND DISCUSSION

Summary of AI Applications in Crop Monitoring and Precision Agronomy

This chart summarizes the distribution of Artificial Intelligence (AI) applications across key functional areas in crop monitoring and precision agronomy. The data highlights a strong emphasis on informational and decision-making systems. Decision Support Systems (25%) and Remote Sensing (20%) are the dominant applications, collectively accounting for 45% of the distribution.

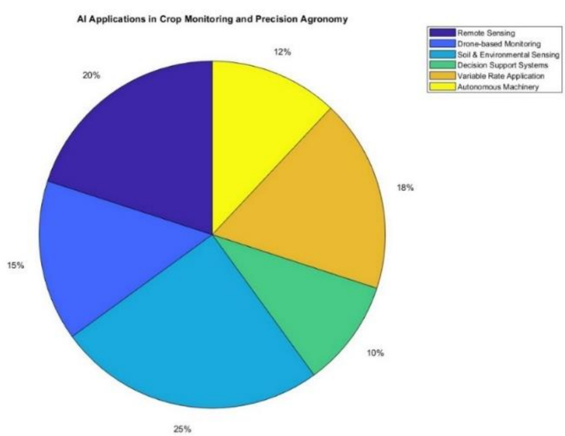

Figure 5. AI Application in Crop Monitoring

Other key areas include Variable Rate Application (18%) and Drone-based Monitoring (15%). The smallest shares are dedicated to Autonomous Machinery (12%) and Soil & Environmental Sensing (10%). The distribution suggests that the current focus of AI implementation is primarily on data analysis, optimization, and remote data collection, rather than ground-based sensing or fully autonomous field operations.

Summary of Key AI Applications in Smart Farming and Precision Agronomy

This bar chart assesses the Impact/Usage Level (on a 0-100% scale) for seven key AI applications in smart farming. All applications show a high level of impact, scoring 75% or higher. The highest impact is found in AI Decision Support Systems (90%) and Yield Prediction (88%). Other high-impact areas include Smart Farming (85%) and Drone-based Monitoring (80%). Autonomous.

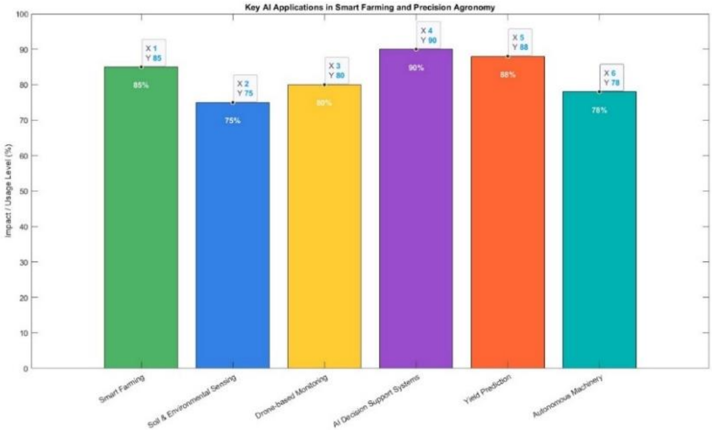

Figure 6. Key Application in Smart Farming Precision

Machinery (78%) and Soil & Environmental Sensing (75%) are recognized as essential, Agronomy foundational technologies, rounding out the high-value applications. The data confirms that the greatest perceived value and usage is concentrated in cognitive and predictive AI tools vital for optimization and planning.

4.1 Distribution of AI Technologies in Modern Agronomy

Summary of Global AI Case Studies in Agriculture

This pie chart summarizes the proportional distribution of documented AI case studies in agriculture across selected countries and regions.

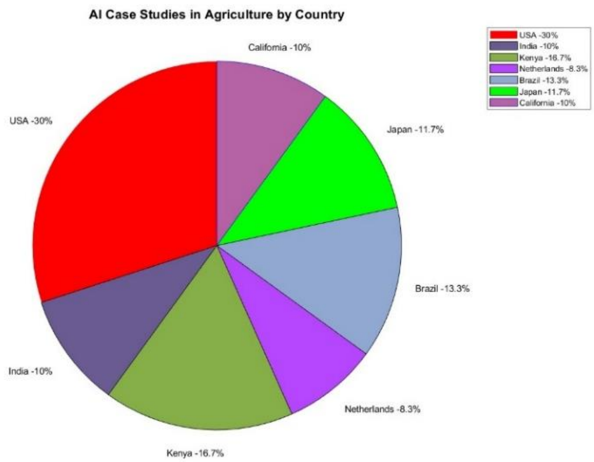

Figure 7. AI Case Agriculture by Country

The USA is the dominant source, accounting for 30.0% of the studies, rising to 40.0% when the specific California (10.0%) data is included. Significant contributions also come from Kenya (16.7%), Brazil (13.3%), and Japan (11.7%). India (10.0%) and the Netherlands (8.3%) represent the smaller portions of the documented examples. In conclusion, the data indicates that North America (USA) leads in the public documentation of agricultural AI case studies, followed by strong representation from countries in Africa (Kenya) and South America (Brazil), suggesting widespread global adoption and innovation focus.

5. CHALLENGES IN AI-DRIVEN AGRICULTURE

While AI has great potential to transform agriculture, its implementation is hampered by several challenges. Poor quality data, poor digital skills of farmers, very high cost of infrastructure, and ethical concerns of data ownership are some of the most prominent challenges.

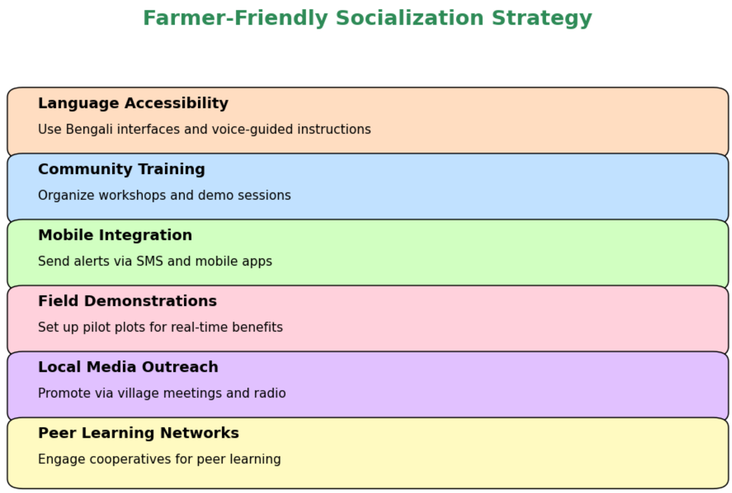

Figure 7. AI Application in Crop Monitoring

Additionally, the environmental impact of AI technologies must be considered for sustainable development. Key Challenges:

- Inconsistent and low-quality agricultural data
- Limited digital skills among smallholder farmers
- High cost of smart tools and connectivity
- Unclear data ownership and privacy risks

  Environmental concerns (e-waste, energy use)

Summary of Farmer-Friendly Socialization Strategy

This diagram outlines a six-step Farmer-Friendly Socialization Strategy focused on promoting technology adoption through accessibility and community engagement. The strategy prioritizes Language Accessibility (Bengali interfaces and voice instructions) and Community Training (workshops and demos). It utilizes modern tools like Mobile Integration (SMS alerts) alongside traditional methods such as Local Media Outreach (radio and meetings). Crucially, the strategy relies on Field Demonstrations for real-time proof and Peer Learning Networks (cooperatives) to ensure sustainable adoption and trust.

CONCLUSION

Artificial Intelligence is transforming agriculture by enabling real-time, data-driven decisions through IoT, sensors, and automation. This farmer-centric system exemplifies how inclusive, affordable AI solutions can empower rural communities, optimize water use, and enhance crop productivity. To ensure equitable adoption, future efforts must focus on improving data quality, infrastructure, and ethical governance making smart farming accessible, sustainable, and resilient for all. Both too much and too little irrigation is bad for agriculture; an "IoT-Based Smart Agriculture Monitoring and Data Analyzing System" might be highly useful for farmers. Threshold values for climatic parameters such as humidity, temperature, and wetness can be determined depending on the local environment. Based on the perceived real-time data from the field and data from the meteorological repository, the author suggests the amount of potassium, nitrogen, phosphorous, which are particularly needed for a crop. The author also suggests how much water is needed for the soil by reading the moisture level. This system develops an irrigation schedule. This technology can tell a farmer whether irrigation is necessary or not. Internet access must be available at all times. Transformation of Agriculture: IoT technology shifts traditional farming to a more efficient, data-driven process. Continuous Monitoring: Sensors enable real-time tracking of soil moisture, temperature, and humidity. Informed Decision-Making: Optimizes resource usage (water, fertilizers) and improves crop yields while reducing costs. Remote Management: Cloud storage allows farmers to manage fields and respond to issues quickly from anywhere. Sustainability and Productivity: Enhances sustainable practices and contributes to long-term farm management. Future Potential: IoT-based systems are key to meeting global food demands sustainably in a resource-constrained world.

Limitations

Although we try our best to make the project as versatile as possible, there are always some flaws in designing these kinds of things. Some limitations of the projectors that the temperature sensor can only measure the surrounding environmental conditions, because of some equipment damage issues, we cannot measure the soil temperature.

It needs human to operate in manual mode. And also set the level for moisture. Sensors may be affected by environmental factors, leading to inaccurate data.

Recommendation & Future Scope

There are opportunities to update this project in the future, such as creating an automated nutrition system can be created which can automatically meet the nutritional needs of all crops in an agricultural field through moderate and balanced distribution of fertilizer. By taking the necessary measures, there is an opportunity to make portable devices with the help of silicon chips. Also, by using a solar system, a power supply can be made into devices that can be used in remote areas. Edge Computing: Faster decision-making by processing data closer to the sensors. Automation and Robotics: Use of drones and automated machinery for planting, irrigation, and monitoring. Block chain Technology: Improved tracking and verification for food safety and transparency in the supply chain. Sustainable Farming Practice: Focus on eco-friendly practices and precision agriculture to minimize waste. Solar system as a power supply unit. An opportunity to make portable devices with the help of silicon chips.

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CHAPTER 3
MACHINE LEARNING: THE FIRST STEP TOWARDS ARTIFICIAL INTELLIGENCE

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INTRODUCTION

Amidst rapid technological developments, artificial intelligence (AI) is now widely used in various fields. Not many people know that artificial intelligence consists of several branches, one of which is machine learning. Machine learning (ML) technology is a branch of AI that has attracted a lot of attention. Why? Because machine learning is a machine that can learn like humans. Machine learning (ML) is a branch of artificial intelligence (AI) that focuses on developing systems that are capable of learning from data on their own. Instead of being programmed manually, machines use algorithms to find hidden patterns in large amounts of information, then use these patterns to make predictions or decisions.

In terms of artificial intelligence, its application is broadly divided into seven branches, namely machine learning, natural language processing, expert systems, vision, speech, planning, and robotics. These branches of artificial intelligence are intended to narrow the scope of AI development or learning, because artificial intelligence essentially has a very broad scope (Panji B., Ratnasari, Edi W., and Andi A., 2024).

Artificial intelligence is a broad umbrella that covers all efforts to create machines capable of mimicking human cognitive functions such as learning, problem solving, understanding language, and making decisions. AI is not just about human-like robots; AI is an intelligent system capable of acting rationally to achieve specific goals.

A simple analogy: If Artificial Intelligence is a car that can drive itself, then Machine Learning is the engine and navigation system that allows the car to learn to recognize roads, traffic signs, and obstacles without needing to be controlled continuously by humans. Machine learning (ML) is a subfield of artificial intelligence (AI) that focuses on developing algorithms and models that enable computers to learn from data and make predictions or decisions without being explicitly programmed.

Machine learning, as an integral part of artificial intelligence, has experienced rapid development and has had a positive impact in various sectors of life, including education. The ability of computers to learn from data and make decisions without explicit programming opens up new opportunities for improving the effectiveness of learning.

This article will explain the importance of machine learning in the world of education, describing various applications that have changed the learning paradigm.

1. A BRIEF HISTORY AND THE INVENTOR OF MACHINE LEARNING

The history of the development of machine learning involves the contributions of many scientists over the past few centuries, specifically beginning in the 1920s. John McCarthy coined the term "Artificial Intelligence" in 1956 at the Dartmouth conference, which is considered the starting point for the field of AI in the 20th century. By creating the term AI, John McCarthy helped define and focus the field of research that includes Machine Learning.

Essentially, the concept of Machine Learning has also existed since the mid-20th century, with several basic algorithms developed during that period. Although the concept had already begun to emerge in the mid-20th century, its rapid development only began in the late 20th century and early 21st century.

In 1959, Arthur Lee Samuel coined and popularized the term Machine Learning. He is often referred to as the pioneer of Machine Learning, and Arthur Lee Samuel is considered a trailblazer and trailblazer in the history of machine learning development. One of the important milestones in the history of ML is Arthur Lee Samuel's work in 1959, which developed a computer program that could learn to play checkers without being explicitly programmed.

- The application of machine learning in education is extensive and varied. One key aspect is adaptive learning, where technology is used to tailor learning content individually according to the student's level of understanding. In addition, student data analysis is an important tool in helping teachers understand student learning patterns and design more effective teaching strategies. Plagiarism detection is also an integral part of maintaining academic integrity.
- The benefits of machine learning in education are significant. Predicting student performance allows for early identification of students who need additional attention, while personalizing education motivates students by providing recommendations tailored to their interests and abilities.

In addition, the use of this technology also supports teacher professional development and more effective online exam supervision. Overall, the benefits of machine learning form the foundation for creating a more adaptive and inclusive educational environment.

2. BASIC CONCEPTS OF MACHINE LEARNING

The basic concept of machine learning involves machines (computers) learning from data to identify patterns or make decisions with minimal human intervention. Unlike traditional programming, where rules are explicitly defined, machine learning uses algorithms to discover these rules independently. Simply put, machine learning (ML) is a branch of artificial intelligence (AI) that enables computers to learn from data without being explicitly programmed for each task. Instead of being given a rigid set of instructions, ML models are fed large amounts of data to discover patterns, relationships, and make decisions or predictions based on that data. This process allows the system to improve its performance over time, similar to how humans learn from experience.

Machine Learning (ML) is a computational method that is a subdiscipline of Artificial Intelligence (AI) that enables a computer system to learn independently and perform tasks by analyzing large data sets without being specifically programmed beforehand. Machine Learning is capable of identifying patterns and trends in data using various algorithms to analyze data and make predictions or decisions. Machine learning technology is a machine developed to be able to learn on its own without guidance from its users. Machine learning was developed based on other disciplines such as statistics, mathematics, and data mining so that machines can learn by analyzing data without the need to be reprogrammed or commanded (Joseph T., S., 2023).

Machine Learning (ML) is a computational method that is a subdiscipline of Artificial Intelligence (AI) that enables a computer system to learn independently and perform tasks by analyzing large data sets without being specifically programmed beforehand. Machine Learning is capable of identifying patterns and trends in data using various algorithms to analyze data and make predictions or decisions.

The basic concept of machine learning can be visualized as a system consisting of three main components that work in a cycle:

Main Components

Input Data: This is the fuel for the learning process. Data can be in the form of numbers, text, images, or sound. The quality and quantity of data are very important for model performance.

Algorithms: These are the “brains” of the learning process—a set of mathematical or statistical instructions that machines use to identify patterns in data. Some examples of popular algorithms include linear regression, decision trees, and neural networks.

Model: This is the result of the training process. A model is a representation of the patterns that have been learned from the input data. Once trained, this model is used to make predictions or decisions on new data.

Process Flow (Learning Cycle)

The machine learning cycle typically follows these steps:

Data Collection: Collecting relevant, high-quality data.

Data Preparation: Cleaning, formatting, and processing the data so that it is ready for use by the algorithm. This is often the most time-consuming step.

Model Training: The (prepared) data is fed into the algorithm. The algorithm repeatedly adjusts its own parameters to minimize errors or maximize accuracy in identifying patterns.

Model Evaluation: The trained model is tested using new data that it has never seen before to assess how well it performs.

Deployment/Inference: If the model meets performance standards, it is deployed in a real-world environment (e.g., in a mobile app or website) to make predictions or decisions automatically [1].

Types of Learning

The basic concept also includes three main types of learning approaches.

Machine Learning (ML) is a fundamental part of Artificial Intelligence (AI) that enables systems to learn from data without being explicitly programmed, allowing machines to recognize patterns, make decisions, and improve their accuracy over time like humans, using algorithms to analyze large data for tasks such as product recommendations, fraud detection, and voice recognition.

The Relationship Between AI and Machine Learning

- AI (Artificial Intelligence): A broad field focused on creating intelligent machines that mimic human cognitive abilities, such as problem solving, learning, and perception.
- ML (Machine Learning): One of the methods or applications of AI that enables systems to learn and adapt from data, rather than through direct manual instruction.
- How Machine Learning Works :
- Input Data: The algorithm receives a large amount of data (which may or may not be labeled).
- Training: The system analyzes the data to find patterns and make predictions or classifications.
- Evaluation (Error Function): Predictions are compared with actual results to measure accuracy.

Optimization: The algorithm adjusts itself (optimize continuous Learning: The more data that is processed, the smarter and more accurate the ML model becomes over time.

3. MACHINE LEARNING: LEARNING FROM DATA

Machine learning learns from data without being explicitly programmed, meaning that a system code does not have to be instructed in detail and continuously on how to perform certain tasks in the program, so that a system does not require maintenance if it is to be used over time to remain compatible with requirements. Before machine learning was invented, these systems were called traditional programs. A machine learning programmer provides data to the Machine Learning system, and the system learns how to perform the task from that data.

Machine learning improves their capabilities without having to be programmed in detail for each task. Machine Learning has recently become popular because it is based on three main pillars, namely:

Big Data: We have generated more data in the last two years than in all of human history.

Computing Power: Modern processors (GPUs and TPUs) are now capable of processing billions of mathematical calculations in seconds.

More Sophisticated Algorithms: New discoveries in technology allow machines to learn with a level of accuracy that surpasses human capabilities in certain tasks.

In this case, machine learning has the ability to obtain existing data on its own command. ML can also study existing data and the data it obtains so that it can perform certain tasks. The tasks that can be performed by ML are also very diverse, depending on what it learns.

The term machine learning was first coined by several mathematicians such as Adrien Marie Legendre, Thomas Bayes, and Andrey Markov in the 1920s, who outlined the basics and concepts of machine learning. Since then, ML has been developed extensively. One well-known example of ML application is Deep Blue, created by IBM in 1996.

Deep Blue is a machine learning program developed to learn and play chess. Deep Blue has also been tested by playing chess against professional chess champions, and Deep Blue won the chess match (Ari M., Kusworo A., and Retno K., D., 2024). Machine learning plays a significant role in assisting humans in various fields. Even today, we can easily find applications of ML in our daily lives. For example, when we use the face unlock feature to unlock our smartphones, or when we browse the internet or social media, we are often presented with advertisements. The advertisements that appear are also the result of ML processing, which provides advertisements tailored to our personal preferences. Machine learning learns from data without being explicitly programmed, meaning that a system code does not have to be instructed in detail and continuously on how to perform certain tasks in a program, so that a system does not require maintenance if it is to be used over time to remain compatible with requirements. Before machine learning was born, this system was called a traditional program.

In fact, there are many examples of machine learning applications that we often encounter. Then the question is, how can ML learn? ML can learn and analyze data based on the data provided at the beginning of development and the data when ML is already in use. ML will work according to the techniques or methods used during development.

5. TYPES OF MACHINE LEARNING

There are several types or techniques used in machine learning, but broadly speaking, ML has two basic learning techniques, namely supervised and unsupervised. For more details, see Figure 1 below (Rozzi Kesuma D., Novia Hasdyna., 2020).

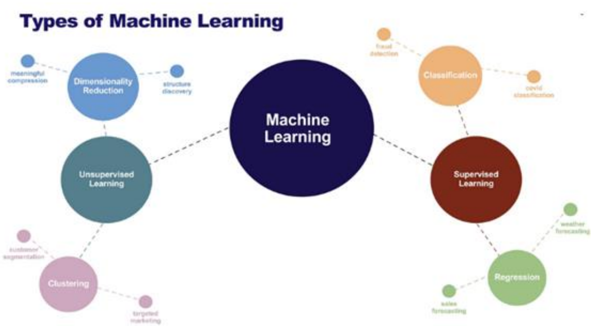

Figure 1. Types of Machine Learning

Based on Figure 1, several types of machine learning can be explained, namely:

Supervised Learning

Supervised Learning is the most common type. This model is trained using labeled data. This means that each data input has a correct answer or output that is already known. The goal is for the model to learn the relationship between input and output, so that it can predict the correct output for new data that it has never seen before. The supervised learning technique is a technique that can be applied to machine learning that can accept information that already exists in the data by providing specific labels. It is hoped that this technique can provide targets for the output by comparing past learning experiences.

Types of Problems Solved

- Classification: Grouping data into discrete categories (e.g., spam or non-spam emails, pictures of cats or dogs).
- Regression: Predicting continuous values (e.g., predicting house prices based on size, number of rooms, and location).

How it works:

- **Labeled Data:** The dataset is divided into inputs (features) and outputs (labels).
- **Model Training:** The model is trained with this data to find patterns and relationships.
- **Evaluation and Prediction:** Once trained, the model is tested with new data to see how accurate its predictions are.

Example: Giving a model thousands of images labeled “dog” or “cat” to train it to distinguish between the two. This is like learning with a teacher who provides the answer key.

Unsupervised Learning

Basic Concept: Unlike Supervised Learning, Unsupervised Learning models are trained with unlabeled data. The task is to find patterns, structures, or groupings hidden within the data itself without the help of output. Unsupervised learning techniques are techniques that can be applied to machine learning used on data that does not have information that can be applied directly. It is hoped that this technique can help find hidden structures or patterns in unlabeled data. Slightly different from supervised learning, we do not have any data that can be used as a reference beforehand. Suppose we have never bought a movie before, but at some point, we buy a number of movies and want to divide them into several categories so that they are easy to find. Of course, we will identify which movies are similar. In this case, let's say we identify them based on movie genre. For example, if we have the movie The Conjuring, we will store The Conjuring in the horror movie category.

Analogy: Imagine we are given a large basket of unclassified fruits. Without being told the names of the fruits, we might group them based on similarities.

For example, grouping all the round and red ones together (apples), and all the curved and yellow ones together (bananas). We identify patterns without external labels.

Types of Problems Solved:

- **Clustering:** Grouping similar data into one group (for example, grouping customers based on shopping behavior).
- **Association:** Finding rules or relationships between items (for example, analyzing shopping carts to find items that are often purchased together, such as “bread and jam”).

How it works:

- **Unlabeled Data:** The model is given raw data without labels.
- **Pattern Discovery:** The algorithm searches for similarities and patterns in the data.
- **Clustering:** Similar data is grouped into new clusters or categories.
- **Example:** Feed the model customer shopping habits and let it discover groups of customers with similar preferences (e.g., customers who frequently buy dairy products and bread). It's like trying to solve a puzzle without the answer key.

Reinforcement Learning

Basic Concept: Reinforcement Learning is the most unique type, where agents (AI models) learn through interaction with their environment. Agents take actions and receive rewards for correct actions and penalties for incorrect actions. The goal is to learn a series of optimal actions (policies) to maximize total rewards over time.

Types of Problems Solved:

- **Control and Robotics:** Training robots to walk, pick up objects, or navigate environments.
- **Games:** Developing AI that can defeat human players in games such as chess or Go.
- **Autonomous Systems:** Training self-driving cars to make decisions on the road.

How It Works:

- **Agents and Environment:** There are agents (models) that interact with the environment.
- **Actions, States, and Rewards:** Agents take actions in a "state" (environmental condition) and receive feedback in the form of rewards or punishments.
- **Learning from Experience:** Agents continuously try different actions and adjust their strategies to maximize rewards.
- **Example:** Training a robot to walk. The robot receives a reward when it successfully takes a step forward and a punishment when it falls. Through trial and error, the robot learns the best strategy for maintaining balance and moving.

ML has become an integral part of the technology we use every day, including:

- **Recommendation Systems:** Platforms such as Netflix, Spotify, or YouTube use ML to analyze our viewing or listening history, then recommend movies or music that we might like.
- **Spam Filters:** Our emails are filtered by ML algorithms trained to distinguish legitimate emails from spam based on word patterns and content.
- **Web Search:** Search engines such as Google use ML to provide the most relevant and high-quality results based on our keywords and search history.
- **Face Recognition:** Our smartphones that can be unlocked with our faces use ML models that are trained to recognize our unique facial features.
- **Virtual Assistants:** Smart assistants such as Siri or Google Assistant use ML to understand voice commands and provide accurate responses.

The way machine learning works actually varies depending on the learning techniques or methods we use in ML. However, the basic principles of machine learning are still the same, including data collection, data exploration, model or technique selection, training the selected model, and evaluating the results of ML.

6. BASIC CONCEPTS OF ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) is the simulation of human intelligence modeled in machines and programmed to think like humans. Meanwhile, according to McLeod and Schell, artificial intelligence is the activity of providing machines such as computers with the ability to display behavior that is considered as intelligent as if that ability were displayed by humans.

In other words, AI is a computer system that can perform tasks that generally require human labor or human intelligence to complete.

AI itself is a technology that requires data to be converted into knowledge, just like humans. AI needs experience and data so that its intelligence can be improved. The important points in the AI process are learning, reasoning, and self-correction. AI needs to learn to enrich its knowledge. The AI learning process is not always directed by humans; rather, AI will learn on its own based on its experience when used by humans (Joseph T., S., 2023).

An interesting thing about AI is that it is capable of self-correction. AI is programmed to continuously learn and correct itself from mistakes it has made.

ML is the main foundation for most modern AI applications. Without ML, many of the breakthroughs we see today would not be possible. ML gives AI the ability to (Widyastuti A., Rahmat P., and Satya A., (2024).

Learn from Data: This is the fundamental ability that distinguishes modern AI from older systems. ML allows AI to adapt and evolve as new data becomes available.

Making Predictions and Classifications: ML enables AI to predict future outcomes or categorize data into specific groups. Examples include predicting stock prices, detecting spam emails, or identifying diseases from medical images.

Building Adaptive Systems: ML-powered systems can adjust their behavior based on feedback or changes in the environment. Examples include self-driving cars that learn from different road conditions or Netflix's recommendation algorithm that tailors suggestions based on users' viewing habits.

In many ways, ML provides the “brain” for AI, enabling it to process information, make decisions, and continue learning, making it the driving force behind the current technological revolution.

7. THE ROLE OF MACHINE LEARNING AS THE FOUNDATION OF ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) is a branch of computer science dedicated to creating intelligent systems that can perform tasks that require human-like intelligence. In AI, machine learning (ML) plays an important role by developing algorithms and models that enable computers to learn and make predictions or decisions independently. Machine learning is fundamental to AI, enabling machines to improve their performance over time through data-based learning.

In this answer, we will explore the importance of machine learning in artificial intelligence and its implications for the future of intelligent systems.

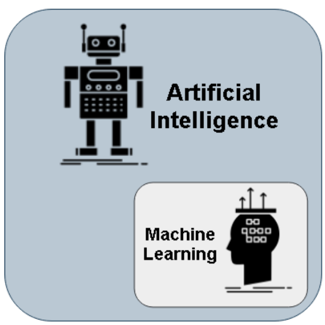

Figure 2. Machine Learning as Part of AI

Figure 2 illustrates that AI and machine learning are interrelated, with machine learning being a part of AI. Machine learning is an important component of AI that enables machines to learn from data and improve their performance over time. By utilizing machine learning techniques, AI systems can analyze large amounts of data, identify patterns, and make accurate predictions or decisions. Machine learning plays an important role in improving the capabilities of AI, making it smarter, more adaptive, and more efficient.

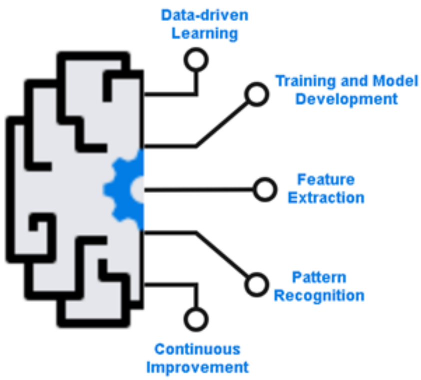

Figure 3. The Role of Machine Learning in AI

Figure 3 can be explained as follows:

- **Data-Driven Learning:** Machine learning algorithms enable machines to identify patterns and extract relevant features by analyzing large amounts of data. These algorithms can also make accurate predictions or decisions based on observed data, thereby improving the capabilities of AI systems.
- **Model Training and Development:** Machine learning plays an important role in training and developing models using both labeled and unlabeled data. Machine learning also allows algorithms to adjust parameters and improve performance over time, resulting in adaptive and accurate AI models.
- **Feature Extraction:** Machine learning excels at automatically extracting meaningful features from complex data types such as images, audio, text, and sensor data. Machine learning provides important information for AI systems for decision-making, classification, and prediction tasks.
- **Pattern Recognition:** Machine learning algorithms learn from past data to identify patterns, enabling AI systems to make accurate predictions, detect anomalies, and classify new events. This is useful for image identification, fraud detection, and medical diagnosis.

- **Continuous Improvement:** The iterative learning process and adaptation of machine learning to new data allow AI systems to continuously improve their performance, increasing their intelligence and efficiency over time. This also makes them more accurate and effective in decision-making and prediction.

The application of AI greatly affects the way we live, interact, and improves our experience and comfort. AI continues to evolve, and there is still much more AI to come in the years ahead. Of course, there will be even better AI with more improvements, developments, and applications.

Broadly speaking, artificial intelligence can perform one of the following four factors.

- Acting humanly, a system that can act like a human.
- Thinking humanly, a system that can think like a human.
- Thinking rationally, a system that is capable of thinking rationally.
- Act rationally, a system capable of acting rationally.

Examples of Artificial Intelligence: Artificial intelligence or AI has been widely applied in various fields such as industry, medicine, education, business, and even in everyday life. Here are some examples of AI applications that we commonly encounter in everyday life (Singgih S., 2024).

Facebook DeepFace

One example of AI is Facebook's DeepFace technology. This AI functions to recognize people's faces in photo posts. With this technology, we no longer need to manually tag people in photos, because the AI will do it for us.

Figure 4. Facebook DeepFace

We may wonder, how does the AI know that the person in the photo is us? It is important to note that before AI can identify that the person in the photo is us, it is trained using data. This data is obtained when we tag people in previous photos and from AI suggestions about people in photos that we approve. After AI is trained and has accumulated sufficient data, it will be able to identify someone in a photo.

Figure 5. E-Commerce Recommendation

One of the most common applications of AI is product recommendations on e-commerce sites. Perhaps you have shopped at an e-commerce site and noticed that certain products are recommended for you. These recommended products are not based on someone's prediction of what we might buy. They are the result of an AI process.

So where does AI get the products to recommend? AI obtains data from us, for example, when we search for products, purchase products, and view products. This data is processed using the AI concept of data mining so that AI can recommend products that are right for us.

Virtual Assistant

Another example of artificial intelligence is the virtual assistant. There are many virtual assistant providers, such as Google Assistant, Siri, or Alexa. Like regular assistants, we can also interact with these virtual assistants. In addition, virtual assistants can record our appointments or events and provide information when the specified event time is approaching.

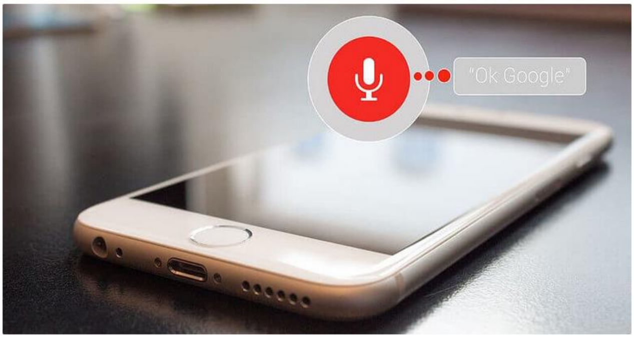

Figure 6. Virtual Assistant

Figure 6 shows that virtual assistants can also be commanded to send messages, play music, open applications, and so on. These virtual assistants will also continue to learn as we use them, so that they can understand what we like and what we usually do.

In fact, there are many more examples of AI applications, such as the AI feature in smartphone cameras that can adjust the camera settings according to the current conditions. Or the AI in Tesla cars that can drive without a driver (Rozzi and Novia H., 2020).

In this case, it can be concluded that Machine Learning (ML) is the main foundation that enables AI to be intelligent and autonomous, as well as AI systems that can adapt and improve their performance over time, similar to how humans learn from experience. This is very important for tasks that are too complex to be programmed manually, such as facial recognition, natural language processing, or medical diagnosis.

8. THE ROLE OF MACHINE LEARNING IN MATHEMATICS

Initially, AI and ML developed as separate fields of study, with AI initially focusing more on symbolic approaches, such as expert systems and formal logic, which did not always involve learning from data. Meanwhile, ML focused on developing algorithms that could learn from data. The relationship between Machine Learning (ML) and Mathematics is not a one-way street.

Mathematics is the foundation that enables ML to work, while ML is a tool that helps mathematicians solve problems that were previously considered impossible.

Mathematics as the Fuel for Machine Learning

Without mathematics, Machine Learning is just a bunch of lines of code without direction. There are three main pillars that build every ML algorithm: Linear Algebra: Used to represent data. Images, sounds, and text are converted into numbers in vectors and matrices. Calculus (Derivatives): This is the driving force behind the "learning" process. Calculus is used to optimize models (for example, through gradient descent) so that the error rate is as small as possible.

Statistics and Probability: These are used to deal with uncertainty. ML works by providing the "best prediction" based on probability, not absolute certainty.

Machine Learning as a Mathematician's Assistant

On the other hand, ML is now used to advance mathematics itself. Theorem Proving: ML algorithms are beginning to be used to help mathematicians find patterns or relationships between highly complex mathematical objects that may be overlooked by the human eye. Symbolic Computation: ML can help solve highly complex differential or integral equations faster through a pattern-based approach, rather than manual calculations.

Geometry and Topology: In modern research, ML helps visualize and classify objects in high dimensions that are difficult to imagine physically.

Turning Numbers into Decisions

Decision Support System: is a machine learning algorithm that analyzes data and provides relevant insights. Decision support systems are used to help experts make better decisions, typically in the medical and financial fields.

Other examples of machine learning applications are:

- **Web search:** ranking pages based on what you are most likely to click on.

- **Computational biology:** designing drugs on computers based on past experiments.
- **Finance:** Deciding who to send credit card offers to. Evaluating risk on credit offers. How to decide where to invest money.
- **E-commerce:** Predicting customer churn. Whether a transaction is fraudulent or not.
- **Space exploration:** Spacecraft and radio astronomy.
- **Robotics:** how to handle uncertainty in new environments. Autonomous. Self-driving cars.
- **Information Extraction**: Ask questions through databases across the web.
- **Social Networks:** Data about relationships and preferences. Machine learning to extract value from data.
- **Debugging**: Used in computer science problems such as debugging. Labor-intensive process. Can suggest where the bug might be.

Key Elements of Machine Learning: Every year, various new machine learning algorithms are developed. Each machine learning algorithm has these components:

- **Representation:** How to represent knowledge. Examples include decision trees, a set of rules, instances, graphical models, neural networks, support vector machines, model ensembles, and others.
- **Evaluation:** How to evaluate candidate programs (hypotheses). Examples include accuracy, prediction and recall, squared error, likelihood, posterior probability, cost, margin, k-L divergence entropy, and others.
- **Optimization:** How candidate programs are generated is known as the search process. Examples include combinatorial optimization, convex optimization, and constrained optimization.

Machine learning algorithms are a combination of these three components, a framework for understanding all algorithms.

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CHAPTER 4
MOBILE APPLICATION–BASED MANAGEMENT OF STUDENT INDUSTRIAL WORK EXPERIENCE SCHEME (SIWES) IN ENGINEERING EDUCATION

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INTRODUCTION

Engineering education is essentially practice-based, whereby learners are supposed to have both theoretical as well as practical industrial competence (Mann et al., 2021). In Nigeria, to close the longstanding gap between engineering education in the classroom and on-the-job experience in the industry, the Industrial Training Fund (ITF) came up with the Student Industrial Work Experience Scheme (SIWES) (Adamu & Musa, 2021). SIWES, as a mandatory course in engineering programmes, introduces students to the practice of engineering by subjecting them to real-life conditions in a professional setting where they can practice engineering tools, techniques, and technologies under practical constraints. Although SIWES is strategically imperative to every higher institution, its management and supervision are largely manual and ineffective, and do not suit the modern digital practices (Nwankwo & Igbo, 2022).

SIWES management is an intricate socio-technical challenge in Computer Engineering that incorporates distributed users, heterogeneous environments, and real-time data exchange, as well as secure information management (Ogunlade & Fagbola, 2020). The conventional method of administration of SIWES involves heavy use of paper-based logbooks, physical visit supervision, and delayed report systems. Such methods are likely to lose data, have improper records, slow feedback, and a lack of transparency. Moreover, the geographic distribution of students in industrial centers complicates the process of constant supervision and, hence, the efficiency of the experience-based learning (Adebayo et al., 2021). Since engineering programs are increasingly focused on digital skills and automation, the persistence of manual SIWES operations can be seen as a major discontinuity between the educational purpose and the administrative action.

The recent developments in mobile computing, cloud services, and cross-platform software development have generated new possibilities to modernise the experiential learning management systems (Islam, 2024). Mobile applications, with a specific regard to this, are portable, accessible everywhere, and in real-time, which makes them particularly appropriate in the context of industrial training when students do not work in standard teaching settings (Segun-Falade et al., 2024).

The learning technology research has also revealed that a mobile-based system has the capability of boosting the engagement of learners, enhancing the efficiency of communication, and providing timely feedback, all of which are essential in the effectiveness of industrial training. These technologies are also used in Computer Engineering as a practical testbed to put into practice such concepts as client-server architecture, mobile software engineering, data security, and human-computer interaction.

The use of smartphones and mobile internet penetration among higher education students has further underscored the argument of mobile-first in higher education (Evanick, 2024). Mobile applications can enable offline data entry, background synchronisation, and notifications as opposed to web-based portals, which may require access to the desktop as well as a reliable connection (Franco, Bidarra, & Henriques, 2025). These characteristics are especially useful in SIWES cases, when students can work in the areas where internet connection is unstable or there is a lack of computing facilities. With the use of mobile technologies, the SIWES management will be able to shift from the reactive paper-driven system to the proactive data-driven system which will facilitate the process of constant monitoring and supervision.

In Computer Engineering teaching, the creation of mobile apps to manage the institution is also in line with the overall pedagogical objectives. Training Students who are trained using such systems are exposed, directly or indirectly, to contemporary software development paradigms, such as cross-platform frameworks, cloud-based backends and secure data handling. Also, the supervisors and institutions have better insight on the student activities, performance patterns and adherence to training goals. All of these advantages can be used to improve the quality of education and graduate preparedness to industry.

Although there are known benefits of digital solutions, currently reported efforts to computerise SIWES management have been predominantly based on simple web-based systems or partial tools like email and spreadsheets. Although these methods will minimize some paper work, they cannot solve fundamental issues associated with mobility, real-time management and integrated data management. Most of the web portals lack mobile device optimisation hence are not well used and adopted by the students.

Moreover, supervisors are not as responsive as they should be due to the lack of real-time notification systems, which affects the pedagogical importance of industrial training.

The chapter discusses the design and implementation of a mobile based SIWES management system which is a computer engineering perspective of the project with focusing on system architecture, mobile software design and the cloud integration. The suggested system will be a substitute of the traditional paper logbook with a secure digital system that will allow recording daily activities, multimedia uploads, real-time communication, tracking of progress, and automated reporting. The application itself is developed with a client and server architecture in which the mobile clients are connected to a cloud-based server to maintain scalability, data integrity and data security.

Technically, the system incorporates some of the fundamental Computer Engineering concepts. These are cross-platform mobile application development, cloud database management, authentication and access control, real-time data synchronisation, and user-based interface design. The interaction of these components to facilitate effective administration of SIWES is shown in the development workflow and system architecture that is illustrated later in this chapter using the development workflow diagram, system block diagram, and application flowchart. These figures give pictorial illustrations of the software life cycle, system modules, as well as functional logic of the application.

This work has its motive not only in administrative efficiency but also in educational influence. The system facilitates reflective learning and timely feedback, which are vital elements of the engineering education that is based on experience through continuous documentation and supervision. Students are stimulated to be active in their training by recording tasks, reflecting on performance, and acting on supervisory feedback almost in real time. Supervisors, on their part, are also able to track progress remotely, detect difficulties at an early stage, and give specific instructions without having to move the logistically heavy physical inspection.

The main goal of the chapter is thus to show how mobile and cloud technologies can be implemented in a systematic way to enhance SIWES management in the field of engineering education.

In particular, the chapter will: (i) examine the shortcomings of current SIWES management solutions, (ii) introduce a technically reasonable mobile application architecture to meet the needs of SIWES, and (iii) discuss the advantages of the suggested system both in terms of education and engineering. The chapter puts the discussion into the context of Computer Engineering and thus demonstrates the importance of software systems as facilitators of effective experiential learning.

The rest of this chapter is organized in the following way. Part 2 is the introduction of the background, theoretical background, and related work, and it focuses on mobile learning theories and current management systems of SIWES. Part 3 is about the system architecture, design procedure as well as implementation specifics, which references the figures obtained based on the developed application. Part 4 includes a discussion of results, limitations, future directions, and a full conclusion, and the complete reference list was prepared in the APA 7 format.

1. THEORETICAL BACKGROUND AND RELATED WORKS

In Nigeria, a national initiative introduced which is the Student Industrial Work Experience Scheme (SIWES), was implemented, aiming at enhancing the practical competence in students studying engineering, technology, and applied sciences. SIWES, which is organized by the Industrial Training Fund (ITF), requires engineering students to spend a certain period of time at an industrial location, which is supervised. The implication behind this is to expose students to industrial equipment, workflow, professional standards, and problem-solving practices that cannot be totally reproduced in academic laboratories. SIWES became a characteristic of the education of engineers in Nigeria over the years and determined their employability and preparedness to work in the industry (Industrial Training Fund [ITF], 2020).

Although it is significant, the operational management of SIWES has not kept up with the changing technological advancements in the engineering practice. The administration of SIWES in most institutions is still dominated by manual operations that include the use of paper-based logbooks, physical handing in of reports, and supervisory visits, so as to make periodic visits.

The procedures are associated with inefficiencies such as slow evaluation, poor records, poor traceability of student activities, and excessive workload on the supervisors. From a systems engineering perspective, SIWES management is a distributed information system that has a wide range of stakeholders, but which is frequently deployed with the drawback of the current digital infrastructure.

The high pace of digitalization of the engineering processes emphasizes the necessity of the same process in experiential learning management. In Computer Engineering, digital systems are commonly created in order to assist distributed users, provide asynchronous communication, data integrity, and real-time monitoring. An extension of these principles to SIWES management to a consistent industrial training administration, makes engineering students gain the same competencies that are being taught during the process. Cloud and mobile-based systems especially offer a viable avenue through which SIWES can be modernised without requiring institutions to have too much infrastructure.

The popularity of smartphones and the use of wireless connections have given rise to mobile computing as a paradigm in modern software systems (Mohiuddin et al., 2022). Mobile apps have become the core of the banking sector, the medical field, the logistics sector, and the education sector, providing services and information accessibility without reference to location. Mobile learning (m-learning) systems have been demonstrated to enhance flexibility, learner autonomy, and engagement, particularly in learning settings with constrained traditional computing resources (Traxler, 2018). These features render mobile platforms particularly appropriate to handle SIWES, in which students are working in various industrial environments, beyond the physical campus.

In Computer Engineering terms, the aspect of mobile application development includes various technical aspects, which are cross-platform frameworks, client-server communication, backend integration, as well as data security. Cross-platform tools have become modern, allowing developers to create programs that can be used on different operating systems using the same code base, thereby saving development cost and enhancing maintenance (Afrihyia et al., 2022).

With cloud-based backends, these systems may facilitate scalability in data storage, authentication services, and synchronisation in real-time between distributed users. These are the systems that underpin the proposed SIWES management system that will be discussed in this chapter.

The theoretical framework of the work is based on the existing learning and technology adoption theories. Constructivist learning theory is one of the most applicable, and it assumes that learners create knowledge actively by reflecting and being in the world. SIWES in design is a constructivist learning exercise because students learn through taking part in actual engineering work and reflecting on their work. This process is elevated by using digital logbooks and feedback systems to offer systems of reflection and supervisor support (Piaget, 1972). The proposed system enhances the reflective aspect of industrial training by digitalising such interactions.

Allied to this is the experiential learning theory, which stresses the cyclical cycle of concrete experience, reflective observation, abstract conceptualisation, and active experimentation. This learning cycle is facilitated by mobile-based recording of day-to-day industrial functions, whereby students record their experiences in real-time and carry out formative feedback, which informs other actions (Kolb, 1984). In this dimension, the SIWES mobile application is not only an administrative tool but a learning support system embedded in the context of the experiential learning process.

Another essential theoretical perspective is the mobile learning (m-learning) theory, which is a continuation of the classical e-learning theory and focuses on mobility, context-awareness, and learner-centred access. M-learning models emphasize the significance of learning and being anywhere and everywhere anytime, being able to use portable devices to help maintain an ongoing learning process (Sharples et al., 2015). Mobile platforms are especially suitable in the case of SIWES students whose learning context is the workplace, not the classroom. The fact that it is possible to document activities, post multimedia evidence, and communicate with supervisors directly at the workplace bears a lot of similarity to m-learning concepts. The Technology Acceptance Model (TAM) also gives an understanding of how digital SIWES systems are adopted.

As it is stated in TAM, perceived usefulness and perceived ease of use are the main factors that influence user acceptance of a technology (Davis, 1989). Most digital systems at the institution fail because they are not usable or the benefits are unclear. When creating a mobile SIWES application, it is therefore necessary to do a thorough consideration in the design to be intuitive, less effort on the part of the user, and value obviousness to both the students and supervisors. This is with respect to Computer Engineering; it has to do with user-centred design, usability testing, and limited evolution.

Also, activity theory helps formulate a valuable model of the analysis of SIWES as a mediated activity system. Activity theory is a theory of the interaction between subjects and goals in a social environment that involves the use of tools. The mobile application in SIWES acts as an intermediation artefact between the students, supervisors, institutions, and industrial organisations. The system reorganizes the activity of industrial training through structuring communication and flow of information, which enhances coordination and accountability (Engeström, 2001). This theoretical approach underpins the incorporation of technological devices in complicated educational processes.

Some studies have already examined how information and communication technologies (ICT) can be applied to SIWES management and industrial training schemes. Initial strategies were based on rudimentary computerisation with the help of spreadsheets or independent databases to hold student records. Although these systems enhanced record keeping, they did not have real-time interaction and, in most cases, were limited to institutional offices. The following internet-based SIWES portals added the option of online logbook submissions and uploading reports, which is a stride in accessibility (Adebayo & Ahmed, 2017). Nevertheless, most of these systems are still desktop-based and not well optimised to be used in a mobile platform.

The recent studies have indicated the possibility of mobile applications in the management of field-based learning and internships. Nowadays, mobile platforms have been implemented in teacher training, healthcare internship, and vocational education successfully, and allow real-time supervision and evidence-based assessment (Kearney et al., 2019). In these studies, there is always an improvement in communication efficiency and learner engagement as well as data accuracy.

Nevertheless, there are not many publications that specifically target SIWES in the Nigerian engineering education system and even less that takes a Computer Engineering approach to the technical design considerations. The mobile solutions available today concerning SIWES are usually characterized by poor scalability, absence of offline functionality or poor security measures. Authentication, authorisation, and data integrity are important issues in a distributed system that involves sensitive academic data. The principles of Computer Engineering offer powerful solutions to these issues, such as ensuring the security of the protocols and controlled access by individuals, and encrypted storage. The system developed in this chapter fills these gaps by considering a structured architecture and design that is security-conscious.

The lack of built-in analytics and visualisation of progress is another weakness of most of the existing systems. In terms of systems engineering, SIWES data is a resourceful opportunity to monitor the performance of students, detect skills deficit, and enhance the process of curriculum updating according to industry requirements. Online solutions facilitate consolidation and examination of this data, which is not achievable with the paper system. Despite the fact that the use of advanced analytics is not the focus of the present implementation, the proposed system is meant to be extended in this direction in the future.

To conclude, the reviewed background and theoretical focus in this section highlight the necessity of a new, mobile-first perspective on SIWES management. The opportunity of constructivist and experiential learning theories to intersect with the mobile learning and technology adoption models offers a solid pedagogical rationale for the proposed system. Concurrently, the loopholes in current SIWES management deals elucidate the possibility of a Computer Engineering-based design that incorporates mobile computing, cloud computing, and secure software architecture. Such considerations are part of the system design and implementation that is detailed below, whereby the technical architecture and development methodology are elaborated, with reference to the system diagrams and workflow figures based on the application that was implemented.

2. SYSTEM ARCHITECTURE, DESIGN, AND METHODOLOGY

Mobile-based SIWES management system design and implementation follow a systematic computer engineering design, which integrates software engineering principles, distributed systems, and mobile computing. Since the participants of the SIWES are geographically distributed, it is necessary to provide the system with the reliability of the data exchange and scalability, as well as the ability to access the system via various levels of user roles. In order to fulfill these requirements, the modular client-server architecture was chosen, which allows the isolation of concerns between the user interface layer, application logic, and data management components.

At the top level, there are three major layers that comprise the system architecture: the mobile client layer, the application services, and the data storage layer. This hierarchical design increases maintainability, scalability, and extensibility, which is critical when designing a computer engineering system. The development process and the interaction between these layers are illustrated in Figure 1 (Development Workflow), which represents the iterative lifecycle used in system development, spanning from requirement analysis to deployment.

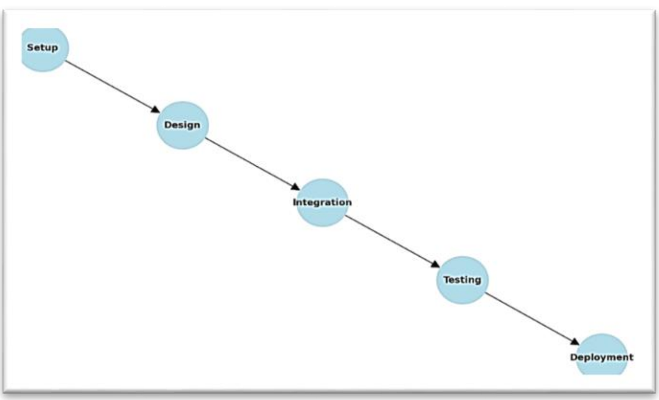

Figure 1. Development Workflow

The student and supervisor applications embedded on smartphones make up the mobile client layer.

These customers will do user interaction, data entry, and local processing. The interfaces were made to be intuitive and with minimum intrusiveness as far as Human-Computer Interaction (HCI) is concerned because SIWES students work in demanding industrial environments. The simplification of input mechanisms was done to help a person use them with less mental effort, and the simplification of the structure of the navigation was aimed at helping one to get to the major functions, including logbook entry, messaging, and reviewing the progress, as swiftly as possible. The mobile customers also have the option of offline functionality in which a user is capable of capturing activities even when offline. Information that is collected offline is automatically synchronized with the backend when communication is re-established, a feature that is essential to reliability in the real-world industrial environment.

The core logic of the system is implemented in the application services layer, which is an application hosted in a cloud platform. This is a mediator layer that lies between mobile clients and persistent storage and also imposes business rules and access control policies. In computer engineering terms, this layer incorporates the concepts of distributed system design, being able to process the requests of numerous users at the same time, yet ensuring the consistency of data. Application Programming Interfaces (APIs) are employed to ease the interaction between the mobile clients and the backend services to make it platform-independent. These APIs handle authentication, submission of logbooks, feedback by supervisors, uploading of reports, and delivery of notifications.

The data storage layer offers centralized and safe storage of all SIWES-based data and information, such as the user profiles, activity logs on a daily basis, multimedia attachments, assessment reports, and a history of communication. The databases were chosen to be cloud-based because they are scalable, fault-tolerant, and available. The relational and document-based models of data organization are used to balance between consistency and flexibility. The encryption of sensitive data and role-based access control are mechanisms that ensure the security of sensitive data by making sure that users can only access the information that concerns their assigned roles.

These security measures are best practices in computer engineering, where the security of data and its privacy are part of the system design. The interplay between these layers is further explained in Figure 2 (System Block Diagram), which demonstrates the functional part of the system and the flow of data between the parts of the system. The block diagram demonstrates that the interaction between student devices, supervisor interfaces, and administrative modules with the backend services occurs via secure channels. The design allows the development of a system in discrete blocks that can be developed and enhanced later, e.g., with analytics or intelligent decision-support modules.

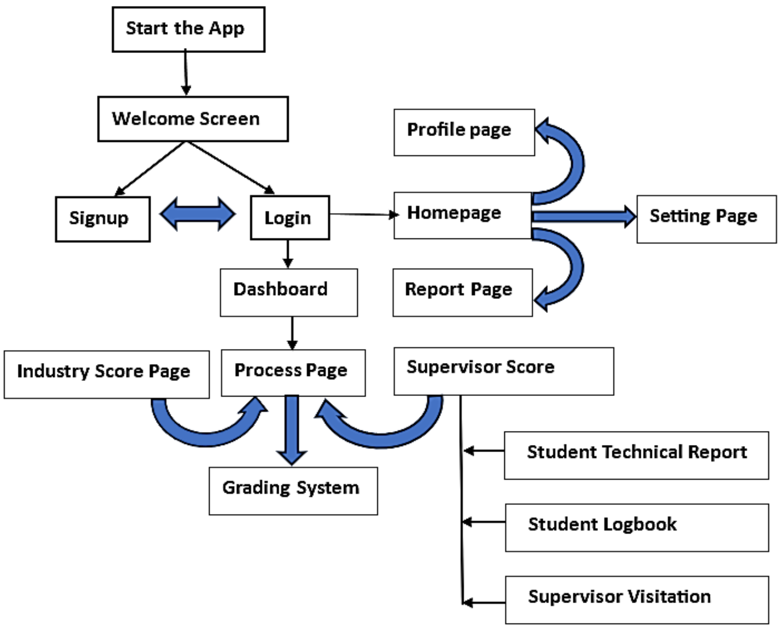

Figure 2. System Block Diagram

The system development was based on an iterative and incremental approach to software engineering. The first requirements were obtained after the consultations with SIWES coordinators, academic supervisors, and students. These needs were examined and converted into both functional and non-functional specifications, like usability, performance, and security constraints. The iterative model enabled the user evaluation of early prototypes, and the feedback enabled future changes in the designs.

It is the approach that is in line with the principles of agile development that are used in contemporary projects of computer engineering. The application logic is illustrated in Algorithm 1 (Application Flow), representing the flow of interactions starting with the user authentication and the submission of the activity and ending with the supervisor evaluation. The flowchart illustrates the way in which the system handles user sessions, authenticates inputs, and manages data storage and feedback. Control flow-wise, the diagram shows points of decision like user role verification and submission approval, which indicate the operation of the system in a rule-based manner. These control mechanisms will guarantee the predictability and safety of the application in various usage cases.

Algorithm 1:

01. Start
02. Display Welcome Screen
03. Prompt User to Enter Login Details
04. Check Login Credentials:
05. If login is valid:
06. Display Dashboard.
07. Proceed to allow access to sections like Profile Page, Report Page, Settings, Student Grading Section, etc.
08. If login is not valid:
09. Redirect to Registration Page.
10. Registration Process:
11. If the user is new:
12. Collect required details.
13. Validate and save the information.
14. Redirect the user to the Login Screen for login with new credentials.
15. Access Control:
16. Based on the user role (e.g., Supervisor, Student, Industry), grant access to the relevant sections.
17. Supervisor: Can access Grading, Progress, Student/Industry Records.

18. Student: Can view Progress, submit assignments, and access personal records.

19. Industry: Can review Reports and Student Records.

20. Allow User Navigation:

Users can switch between sections like Dashboard, Profile Page, Grading, and Reports.

Actions such as Submission and Grading updates are available based on user permissions.

21. End Session or Logout:

The user can log out from the Settings Page or by selecting the Logout option.

22. Stop

The digital logbook module is one of the functional modules of the system. This module will eliminate the paper logbook system in favor of a systematic electronic system that will accommodate text, images, and time-stamped entries. The activities and tools employed in the industry daily, along with skills learned, are recorded by students and serve as a rich source of assessment and reflection. Data engineering-wise, every logbook record is connected to metadata (i.e., date, location, and supervisor status) and can thus be easily queried and retrieved. Formative assessment can be supported through supervisors who can review entries remotely, make comments on them, and ask to make changes or approve them.

The communication module facilitates real-time and asynchronous communication between the students and the supervisors. In this module, messaging and notification services have been incorporated to provide feedback and guidance in time. Push notifications remind supervisors of new submissions and tell students whether they have been approved or not. In systems of distributed learning, real-time communication plays a pivotal role in keeping the activity interactive and allowing information to be delivered in a consistent manner. This module design is based on the concepts of networked systems, in which the latency, reliability, and user experience should be well-balanced.

The assessment and progress tracking module is another important component, and helps in the constant assessment of the performance of the students. Supervisors may give ratings or qualitative feedback on logbook records, whereas students are able to see their progress via visual feedback. Systems-wise, this module integrates personal records of activities into the records of high-level performance to allow supervisors and administrators to track training performance. Even though basic analytics is applied in the existing version, it is designed to support advanced data analysis methods in the future, including performance prediction and anomaly detection.

The system design has security considerations as a key factor. Authentication mechanisms prohibit unauthorized users from accessing the platform, and the ability of the user, depending on their type, is governed by role-based access control. The secure communication protocols ensure the security of the data exchanged between the mobile clients and the backend services. Such steps are necessary in protecting academic documents and ensuring credibility to the system. Such security considerations are not optional features added during the design of computer engineering but mandatory requirements.

The deployment plan is using cloud infrastructure to have high availability and scalability. Cloud hosting allows the system to support different numbers of users without the institutions making substantial investments in local infrastructure. Backups and redundancy systems work automatically, which improves the reliability of the system, and the chance of loss of data is minimized. This deployment model is a special type that is applicable in educational establishments with limited IT resources since the management of the infrastructure is transferred to the service provider.

To conclude, the system architecture and design discussed in this section show how the principles of computer engineering can be used to solve the real-world problems in the management of SIWES. The proposed mobile application offers an effective and scalable solution to managing industrial training by implementing a layered client-server architecture, an iterative development approach, and cloud-based deployment with an appropriate level of security.

The abovementioned figures development workflow, system block diagram, and application flowchart are all elements of the technical coherence of the system and its conformity to the current software engineering standards. It is based on these design choices that the effectiveness of the system will be determined, and these choices will also be used to discuss the results, limitations, and future improvements that will be discussed in the last section of this chapter.

3. DISCUSSION, CONCLUSION, AND FUTURE DIRECTIONS

The application of the mobile-based SIWES management system evidences that the computer engineering principles may be successfully used to solve the problems that have long been inherent to experiential engineering education. The system offers efficiency, transparency, and scalability to SIWES administration by replacing the manual and paper-based process with a digital and mobile-first platform. The findings in this section are based on system deployment, functional testing, and user feedback gained within the period of analysis and development phases.

On the operational aspect, the system will greatly enhance documentation and oversight of industrial training activities. The digital logbook module allows students to document their daily activities in a time-and-date-ordered way and decreases the chances of incomplete or falsified entries, which is mostly the case with paper logbooks. These records can be accessed remotely and in near real time by the supervisors, and therefore, continual monitoring can be done as opposed to end-of-training evaluation. This recommendation to replace summative with formative supervision is consistent with the best practices in the field of engineering education, where continuous feedback is necessary in skill development.

Figure 3 (Supervisor Module) is the supervisor dashboard, and it is the key control interface for the academic supervision of the system. The module also shows the information of the supervisor profile, departmental membership, and institutional identity, hence accountability and traceability of the supervisory activities.

The dashboard is also equipped with an overview of assigned students and pending reviews so that the supervisors can prioritize their work most efficiently. In terms of computer engineering, this module is also illustrative of good role-based interface design, where the functionality of the system is narrowed down to the duties of the user. The fact that there are real-time status indicators indicates the event-driven nature of the system, as the supervisors can receive instant feedback on the actions of the students and respond accordingly.

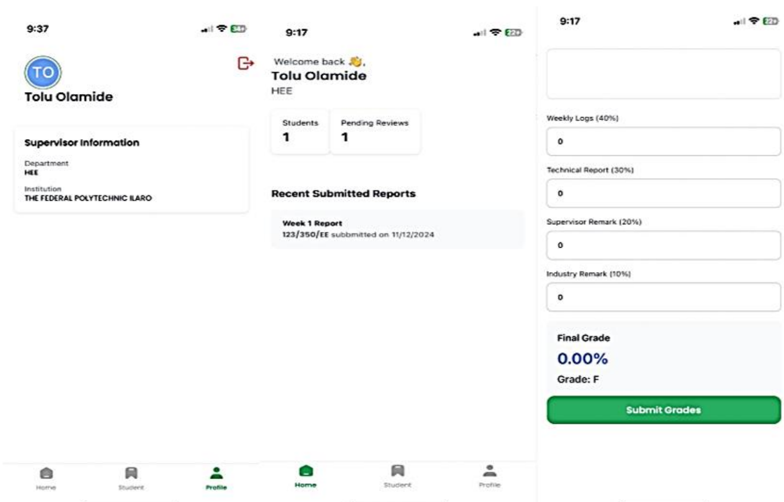

Figure 3. Supervisor Module

The student access control and authentication interface is displayed in Figure 4 (Student Login Management). This number demonstrates the fact that the system is concerned with security and controlled access since students must authenticate to access SIWES functionalities. The mechanism of login management is combined with the services of backend authentication, as a result of which only registered and verified people can view training records and submission tools. In terms of system security, this element implements identity verification and session management, which are critical elements in the protection of academic records and integrity of data in distributed mobile applications.

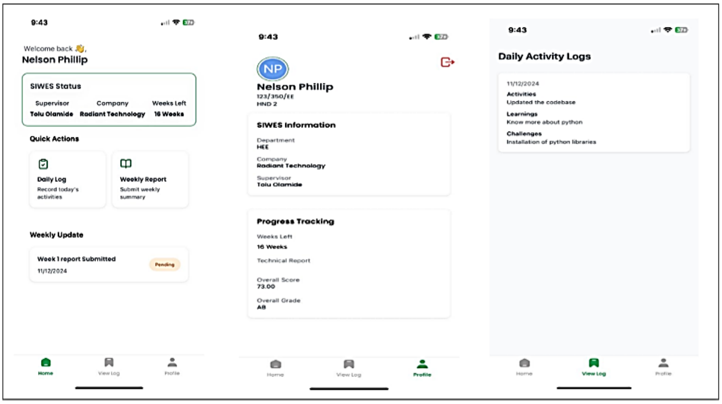

Figure 4. Student Login Management

The procedure of recording industrial activities is also depicted in Figure 5 (Student Weekly Report Creation and Submission). This interface will enable the students to organize and submit structured weekly reports on activities done, the tools, work difficulties, and skills learned. The system has an incremental submission and revision, which allows students to revise entries prior to ultimate approval. Computer Engineering In this module, this is an illustration of form-based data capture combined with backend validation and storage service. The organized format of reporting increases consistency of data and automated evaluation and retrieval of data, which is impractical using the traditional handwritten reports.

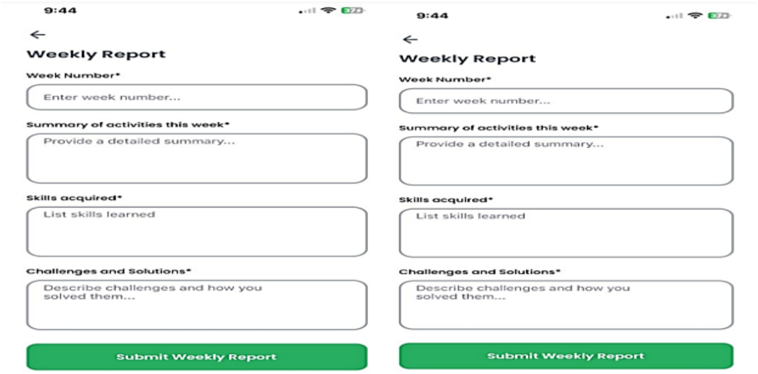

Figure 5. Student Weekly Report Creation and Submission

The accessibility and user onboarding are supported by the registration interfaces represented in Figure 6 (Signup Pages). The pages allow new users to open accounts in the system with the necessary personal and institutional information. It is designed in a simple and clear way to minimize friction in the onboarding process, especially among people with different degrees of digital literacy. The software engineering side of this component is that it is an embodiment of user-centered design and validation logic to minimize the occurrence of incorrect or insufficient data entry during the registration process.

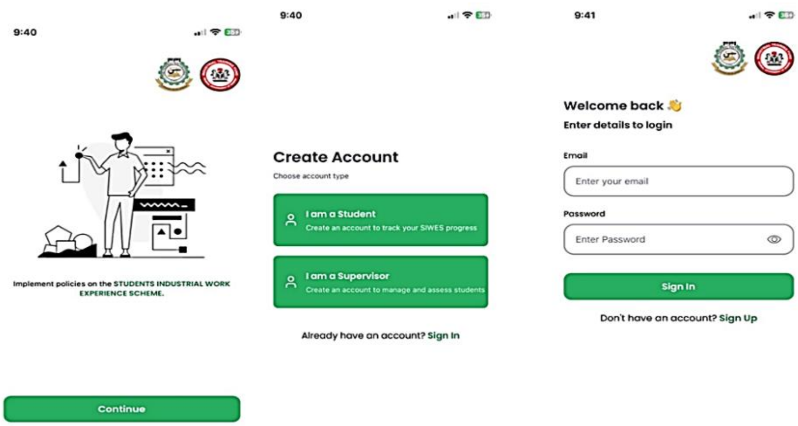

Figure 6. Signup Pages

Figure 7 (Student and Lecturer Signup Pages) also goes a step further to extend the onboarding process by separating user types when creating an account. Different registration options for students and lecturers will make sure that the right permissions and system rights are granted automatically. Such a registration system allows easy administration of systems based on roles and also minimizes configuration errors. Such role differentiation is essential in practice in multi-user systems in computer engineering, which implements access control policies as early as possible and improves the security and maintainability of systems.

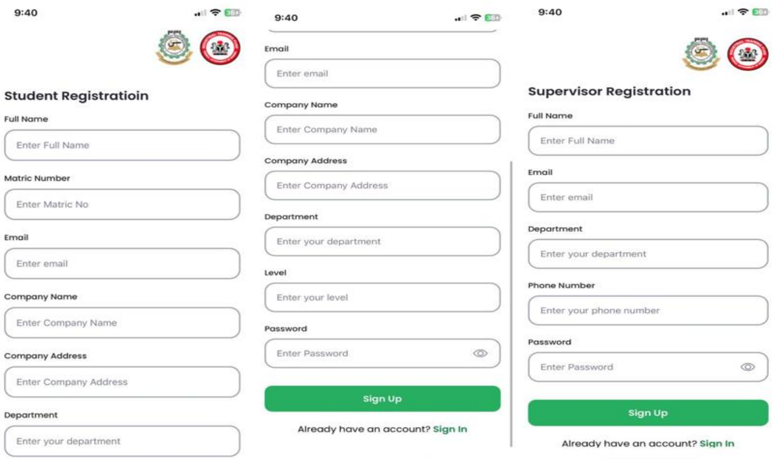

Figure 7. Student and Lecturer Signup Pages

The communication module also increases the level of effectiveness of the supervision process as it allows direct communication between students and supervisors regardless of physical location. In-app feedback, in the form of messages and notifications, replaces students with timely feedback and helps them fix mistakes, improve their techniques, and align their activities in the industrial environment with the academic learning outcomes. Regarding systems engineering, this real-time communication minimizes latency in the feedback loop, which is a highly important performance metric in distributed learning systems. The increased responsiveness, which is evident in the process of using the system, highlights the importance of mobile communication technologies in the management of the field-based learning environments.

The evaluation of the progress and assessment are the characteristics that help to introduce enhanced transparency and accountability to the evaluation of SIWES. Supervisors have an option to review activity logs in real time, give ratings, and give qualitative feedback, and students have the opportunity to see their performance trajectory. This mutual visibility creates a sense of responsibility and mobilization of the students, which will make them participate regularly during the training process. In comparison to the conventional methods of SIWES assessment (where final reports and minimal interaction with supervisors are usually used), the proposed system promotes the idea of evidence-based assessment based on daily performance data.

Regarding computer engineering, the system can be used to demonstrate how client-server architecture, cloud computing, and mobile software engineering can be put into practice in an educational setting. Platform independence and modularity through the use of APIs to do mobile-to-backend communication allow future expansion. The layered architecture allows the implementation of changes to any single component, e.g., the user interface or the database schema, without having to affect general system functionality, and therefore makes it more robust and maintainable.

The key concerns during the system design were security and data integrity. The authentication system, role-based access control, and transmission of encrypted data make sure that the sensitive academic and personal information will not be used by unauthorized people. These characteristics are also of paramount importance in institutional systems that handle assessment documents and identity data. The effective merging of these protective measures is an indication of the fact that computer engineering solutions have the ability to strike a balance between usability and security; this has been a recurrent problem with mobile and cloud-based systems.

In spite of these strengths, there are limitations of the system too. The reliance on mobile phones and internet connectivity is still a limiting factor, especially in industrial settings where the network connection is not very stable. Despite the fact that offline data entry is supported, synchronization can be delayed, and this aspect can impact real-time supervision. Moreover, digital literacy disparities between users can affect adoption levels, and this is why the issue of user training and institutional support is significant.

Multiple-institutional and industrial partner scalability is also problematic. Although the cloud-based architecture in theory can support mass deployment, it would need to coordinate activities between institutions, industry supervisors, and regulators like the Industrial Training Fund. They would need to be interoperable and consistent through standardization of assessment criteria, reporting formats, and data exchange protocols.

The system has great prospects of improvement in the future. The combination of data analytics and artificial intelligence may make it possible to perform intelligent supervision, predictive performance analysis, and automatic feedback.

Moreover, the identification of the location and context could allow some additional validation of industrial processes and add to the data of experiential learning. Connection to institutions' learning management systems and national SIWES databases would also help to simplify administration and assist in making data-driven decisions in educational policy.

To conclude, this chapter has shown how industrial training administration can be modernized using a mobile-based SIWES management system, which is based on the principles of computer engineering. The system can facilitate more effective experiential learning by enhancing the accuracy of documentation, efficiency with supervision, and transparency in assessment as well as efficiency in communication. In addition to its immediate use, the system offers a scalable and extensible system of digital innovation in the field of engineering education, supporting the importance of computer engineering in addressing real-life educational issues.

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ISBN: 978-625-93129-8-9