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Comparative Performance Analysis of Machine Learning and Deep Learning Models for IoT-Based Crop Yield Prediction

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Abstract

The environmental uncertainty and the nonlinear behaviour of IoT-sensor data nature influence the crop yield prediction. In Nawab Shah, this region requires a model which behaves capturing complex patterns. This study provides a deep learning and machine learning comparative analysis, whereas data is obtained from the IoT-based sensor data; the dataset parameters include temperature, humidity, smoke, and light intensity. The dataset has more than 35000 time-stamped samples, collected with the five seconds delay in each data reading. These observations are processed by applying data normalisation, outlier detection and cleaning, and min-max normalisation. The statistical data validation is obtained by applying RMSE, MAE, MSE, Pearson's correlation and confusion matrix. The Bayesian-optimised random forest consistently achieved outstanding performance with the highest accuracy, recall, and precision with 0.33 F1-Score. The smoke and humidity are the significance factor from the obtained results analysis for the yield prediction. The classification ability is confirmed by the confusion matrix with the ability as average, good and poor classes of the yield. Furthermore, the finding shows that the optimised random forest performed better than all in the environmental data for the prediction of yield. This is also based on the same features as smoke and humidity; this methodology and approach provide a reliable and low-complex framework with a real-time precision agriculture system for decision-making. LSTM models, along with a variant of Random Forest, give results of 0.27 intermediate range value, which recommends that the very important patterns are captured, but are not effective for the top models.

Keywords: yield prediction, Smart agriculture, machine learning and deep learning

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Introduction:

The agriculture sector in Nawab Shah, Sindh, Pakistan, is very crucial. The crop yield can be affected by soil conditions, irrigation availability, and other factors. The sustainability of the crop productivity is based on the different environmental and soil conditions. The conventional methods provide late observation and a lack of precision in the context of decision-making. The variable which are crucial for the yield production are weather and soil. The data collection regarding related parameters is a very crucial step. The data patterns obtained from the sensor are very important for future decision-making. This sustainability can be affected by the different factors that also influence the yield estimation. This region needs to transition from the traditional methods to data-driven decisions on the basis of agricultural data, which can help for the optimized decision making with sustainable farming. A few IoT based system provides the different variable depth recording directly with integration of the real-time sensor modules. This IoT-based module helps to monitor the real-time environment with effective methods of a data-driven approach. The critical factors like temperature, humidity, light intensity and other important factors can be monitored by deploying an IoT-based infrastructure.

Machine learning (ML) is a subfield of artificial intelligence (AI) which deals with designing and creating systems that improve their functionality via experiential learning, as opposed to explicit programming of specific tasks (Saini et al., 2024). Machine learning has its conceptual roots in the middle of the twentieth century, as scientists struggled to provide computers the ability to learn in a similar way as humans. The capacity of a computer to learn without the need to be taught explicitly was defined by computer scientist Arthur Samuel as machine learning in 1959, thus forming the theoretical basis of the field. In the last 50 years, machine learning has come out of crude pattern-recognition methods to an advanced discipline that integrates concepts of mathematics, statistics, and supercomputers. At its simplest, machine learning assumes patterns in the data and that the patterns are useful in algorithmic prediction of future events. The main difference between machine-learning models and old-fashioned rule-based systems is that the former is a data-driven learning model, which is not based on a pre-defined set of rules, as the latter is. The learning algorithm builds an internal model of the relationship between inputs and outputs by sequentially optimising model parameters, in order to maximise predictive accuracy, by using a set of historical exemplars (Mirani et al., 2023). As a result, the model learns how to perform classification, regression, clustering, and decision making, and it improves with time due to the learning mechanism that it inherently has. This flexibility of the machine-learning models is a significant strength, as it allows the model to be continually optimised to work with new data streams and improve the predictive accuracy. The main element of many modern intelligent systems is machine learning at the moment. Examples of the scope of domains with applications of ML methodologies include speech recognition, visual perception, recommendation engines, predictive analytics, and completely autonomous technologies. With such a large amount of digital data and access to significant computational capabilities, machine learning is now used in practically all parts of the economy. It is the ability to convert raw data into actionable information that makes machine learning one of the core technologies that form the basis of the digital transformation and the age of intelligent automation.

Current Trends and Future Directions

Today's industry sees machine learning (ML) evolving from narrowly focused, task-specific solutions to generalised, flexible, and highly efficient solutions. A major trend is that the field is developing large foundational and pre-trained models and allowing them to be fine-tuned for multiple tasks with limited additional data. (Shaikh, 2019). Self-supervised and few-shot methods are being developed to reduce dependency on large-scale labelled datasets, thus providing greater accessibility to ML technologies in domains with minimal annotated data. Simultaneously, multimodal learning is being developed, which allows models to process and integrate different types of data (text, images, audio, sensor) within a single framework. Another key trend is the focus on developing responsible and accountable AI. Researchers are investigating ways to improve learning techniques, including fairness, transparency, robustness, and privacy preservation, to create ML models that are open and socially responsible. Federated learning and edge AI are driving ML implementations into decentralised environments, providing real-time analysis of data while protecting sensitive data. (Karim et al., 2018). Likewise, there is ongoing research on reducing the carbon footprint and environmental impact of large-scale ML models. The future of Machine Learning (ML) will continue to shift toward building ML systems that are accurate, adaptable, interpretable, and resource-efficient. One way this can be accomplished is by integrating the new technologies emerging today - quantum computing, advanced robotics, and next-generation communication networks - with ML. This advancement in ML capabilities will also be supported through the continued evolution of ML with collaborative research efforts across a wide range of fields (such as computer science, statistics, engineering, ethics, and public policy) to guide ML development towards innovative new solutions that will have a real impact on society.

Conceptual Synergy between IoT and ML

The idea behind the Internet of Things (IoT) and machine learning (ML) being conceptually synergetic implies that the functions of each field complement each other and are complemented by those of the other (Nawaz & Babar, 2025). The IoT is a system of interrelated devices, e.g., sensors, smart appliances, cars, and industrial equipment, which constantly produce large amounts of data. Nevertheless, the unstructured and unfiltered information generated by the IoT is often noisy and large, hence making it difficult to extract any meaningful insights without using advanced analytic algorithms. Machine learning provides the tools and capability to process, analyse, and learn this data to be able to make intelligent decisions, predictive maintenance, detect anomalies, and automated control in the IoT ecosystem (Nawaz & Babar, 2025). The integration of the IoT and ML is very effective, as the ML algorithms can be easily introduced to the IoT infrastructures to make it possible to engage in real-time analytics and responsive actions. To use the example of smart-city implementation, IoT sensors can produce data about traffic and pollution, energy use, which in turn can be analysed with the help of ML algorithms and allow optimising the traffic flow, reducing pollution, and allocating energy more effectively. Similarly, in industrial IoT (IIoT) environments, predictive maintenance models based on ML can detect a fault before it happens in equipment and allow taking urgent actions to minimise downtime (Zafat et al., 2025). This conceptual synergy, therefore, turns the IoT into something beyond a data-gathering platform, into an intelligent and autonomous system, which can learn, adapt, and optimise its own operations dynamically.

Data Flow and Learning in IoT–ML Ecosystems

The integration of the Internet of Things (IoT) and machine learning (ML) has a certain lifecycle that implies data acquisition, processing, and analysis. Data Acquisition is achieved by IoT, which produces vast volumes of different data, including temporal, geographic, and contextual. (Klein et al., 2024). The Data Transmission proves are relayed using one of the protocols like MQTT, CoAP, or 5G networks to edge or cloud computing services. Whereas data Processing and Analysis is achieved by the ML algorithms can be executed at the edge, where they are used to make low-latency decisions, or in the cloud, where they are used to analyse a large amount of data. Learning and Prediction (Muruganantham et al., 2022) part is basis on models are trained to identify trends, categories, patterns or forecast the results, like equipment breakdown, crop yield or energy consumption.

ML models are used to provide feedback and actuate results, so as to provide a closed-loop intelligent system. This structure fosters efficiency of operations, utilisation of resources, and predictability and eventually results in a self-developing environment that responds dynamically to real phenomena of the world.

8.3 Applications of IoT–ML Integration

The intersection between the Internet of Things (IoT) and machine learning (ML) has given rise to the growth of various areas, as shown in the following areas:

Smart Agriculture (Arslan et al., 2023)(Dayoub et al., 2024)(Mirani et al., 2021) It is a vast field and providing several opportunities. Continuous observation of soil, climatic, and crop indicators makes it possible to use the ML algorithm to predict crop yields, diseases in plants, and irrigation optimisation. Smart Healthcare applications also provide extensive applications. ML algorithms are used to analyse physiological parameters collected by wearable devices and predict possible health abnormalities, and to provide customised treatment plans. The Industrial Automation (Industry 4.0) (Memon et al., 2025) The emerging field of ML-based sensor input analysis helps predict the maintenance needs and can be used to optimise quality control in the industrial environment. Smart Cities (Al-Sammak et al., 2025) covers different applications using IoT systems in cities, combined with ML, will improve traffic and energy usage, waste collection, and the delivery of services to the population. Energy systems (Pallavi & Prasanna Kumar, 2025)Provided by the integration of the machine-learned load prediction and grid stability, as well as the renewable-energy resource management, are optimised with the help of data analytics provided by the IoT. Those illustrations indicate that the combination of IoT and ML can provide contextual intelligence, hence enhancing efficiency, sustainability, and human welfare.

Revolution and Challenges of IoT–ML Convergence

The combination of machine learning (ML) and the Internet of Things (IoT) has several benefits that include:

Better decision-making provided by the data-driven insights will help in predictive and proactive decision-making (Hernández Hernández et al., 2025). The Automation and optimisation by ML algorithms are used to automate processes and reduce the human factor and expenses. In addition, the system is dynamically learned as a result of changing environments and user behaviour. Scalability and integration of Cloud infrastructure allow the use of IoT networks to scale easily. However, this integration is also faced by several challenges, including data privacy and security, which focus on ongoing data transactions between the devices and the cloud, which are a threat to the privacy and security of data. Computational limitations are very challenging due to the limited computing capabilities of edge devices. (Yang et al., 2025), which is a significant barrier to the computation of sophisticated machine learning operations. Interoperability issues often create many problems in IoT systems. IoTs are generally heterogeneous in devices and communication protocols, which is not always standardised. ML models that have been trained in one specific setting might not be effective in generalising to new settings. To deal with these issues, it is necessary to develop light ML algorithms, powerful data infrastructures, and standardised IoT communication protocols. These research directions are increasingly becoming popular in both academic and industrial circles.

Novelty and Scope of Study:

1. Most of the researchers have used a generic dataset or a public library dataset, whereas our study provides an IoT-based, real-time dataset of a specific region. The agro -climate condition is obtained from data related to the specific IoT sensors. In this region, Nawab Shah, the climate is very harsh in this season and has a direct impact on the yield. Therefore, this data is very crucial for the yield prediction, which has not been focused on before. Furthermore, the validation of the data is also performed to ensure ML models' performance for climate adaptation.
2. The Bayesian optimisation is not focused on the same dataset before, with calibrating these models for the yield prediction based on the real-time data obtained by the deployed sensors Module.
3. Whereas the crucial part is interoperability, which is based on different factors. We expanded the analysis phase with in-depth insight into how the different variables impact the yield.

Research questions:

Q.1 What type of classification models are required to train this data? Which model results in the highest score of predictive accuracy?

Q.2 How do Bayesian hyperparameters enhance the performance by applying optimisation as compared to the traditional ML/DL models?

Q.3 What did the study reveal after traditional ML and DL models comparison in the context of predictive metrics?

Objective:

1. To investigate the impact of the crucial weather and soil factors on the crop yield
2. To collect data for the cotton crop season, and to collect weather and soil data parameters.

3. To train and test ML models comparatively for the yield prediction and classification

Methodology:

Data collection:

Data is obtained from Kaggle, which is an IoT-based module data collected. In this regard, the data is about the weather and soil data. The different data points are used by data preprocessing, as discussed below in detail.

Annexure (A)

Data is collected from the IoT sensor-based module, which is used for the sensor data of the weather. The sensor data is obtained to prepare the datasets, and parameters include temperature, humidity, light intensity and smoke. These parameters are very crucial from the seedling to the final yield production. The data set is prepared for the cotton crop season, which is from May 2025 to August 2025. The data is collected from the Nawab Shah district of Sindh province, Pakistan.

Annexure (B)

Figure 2 presents the complete scenario of the data collection to data visualisation. A further IoT-based module is used for the data collection. Data processing is also used for data validity and cleanliness. The field area is also shown to collect data from the cotton crop field. Data collection is performed by the IoT-based sensor, giving details. Table 1 below presents the sensors connected with the Arduino Uno and having a pin connection type. The detail shows the pin connection of each sensor type with the Arduino Uno microcontroller board.

Table 1: Sensor type, name and connection pin

Sensor type	**Sensor Name**	**Arduino Pin type**
Soil moisture	Capacitive/resistive	Analogue (A0-A5)
Temperature	DS18B20/DHT11/DHT22	Digital
Humidity	DHT11/DHT22	Digital
Light intensity	LDR	Analog
Soil pH	Analogue pH sensor	Analog
Rainfall	Rain Gauge	Digital Input

Data Preprocess:

In this study, the data preprocessing is performed on the obtained sensor data. The data cleaning is applied to incomplete data readings or having half-reading values. These values are removed or reset manually. The data arrangement is based on the parameters data, which is also set as needed.

Handling outliers:

The sensor data is obtained and preprocessed under three stages:

1. **Outlier handling**: the fluctuations in the environmental IoT-based data, the identification of anomalies and outliers are explained by checking the output values within the examined range. We removed values that are not in the range of the Nawab Shah environment, such as temperature, humidity, smoke and light intensity. The range is removed if found out of bounds.
2. **Normalisation and feature scaling:** the Min and Max normalisation is applied to the normalisation features, which range from [0,1]. This is important to range the large values in to avoid from the disproportionate influence, which influences the weight of the model, which shows the sensors are contributing properly to the prediction of yield.
3. **Data set organisation":** the training and testing dataset is split using a range of ratios, 80:20. This provides the unseen data assurance for the model evaluation, which helps to provide an unbiased assessment of the

generalisation.

Model selection:

In this study, a few of the models are selected to compare on the same dataset to predict the yield. The SVM, CNN, LSTM, RandomizedsearchCV, CV-optimised Random Forest, Gradient boosting and XGBoost. These models are implemented on Google Colab using Python. The basic machine learning and deep learning libraries used numpy, pandas, TensorFlow, matplotlib and state. The comparative analysis is performed to evaluate the traditional models and the optimised version of the model on the basis of different machine learning model performance parameters.

Why is the LSTM Model used:

The long short-term memory (LSTM) is inherent of recurrent neural network (RNN), designed to interpret the sequential data for the avoidance of the limitation of the RNNs. This is due to the focused of vanishing and exploding gradient problems. The LSTM mathematical formulation and sequences by maintaining a hidden state are given below:

$H_t = \tanh (W_h h_{t-1} + W_x x_t + b)$

However, when sequences are long:

1. The vanish state is a model that forgets earlier information
2. The exploding gradient is the mode when the unstable training process behaves

The basic principle of the LSTM is followed by introducing a memory cell + a gating mechanism.

The core idea of the LSTM model is to use the cell state C_t, which acts as a memory highway, in which information flows unchanged over long distances. The LSTM gates are used to control what to remember, forget and output, which is a basic principle.

(a) LSTM architecture:

1. Cell state C_t:

The LSTM cell state is presented by the C_t, which is used for the long-term memory and carries information across the time steps.

2. Hidden state h_t:

The LSTM model presents the hidden state as h_t with short-term results output, as used for the prediction. Further, the LSTM have three gates, which are the forget gate that decides the memory discarded process, and the filtration.

$f_t = \sigma (W_f [h_{t-1}, x_t] + b_f)$

LSTM output range is given as: (0,1), which shows 0 is for forgetting completely and 1 means keep everything for the saving states.

3. Input Gate:

The input gate in the LSTM model is used to decide which new information is used to store, as given mathematically below

$i_t = \sigma (W_i [h_{t-1}, x_t] + b_i)$

whereas the LSTM model candidate memory is presented mathematically as

$C_t = \tanh(W_c [h_{t-1}, x_t] + b_c)$

4. Update Cell state:

The LSTM Model updates the state of the cell as given below mathematically

$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$

The equation depicts the core innovation of the LSTM model, which is actually for the old memory, and the new memory is selectively added.

5. Output Gate:

The output gate in the LSTM model is presented mathematically as below in the equation.

$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o)$

Final hidden state:

$h_t = o_t \cdot \tanh(C_t)$

Experimentation and Data Evaluation

For the experimentation, the data is evaluated, and model comparison is performed. The measure of tendencies, correlation values are measured to compare the model performance on the same dataset. The parameters are precision, recall, accuracy and F1 score. The comparative analysis graph is shown In the graph, Figure 1:

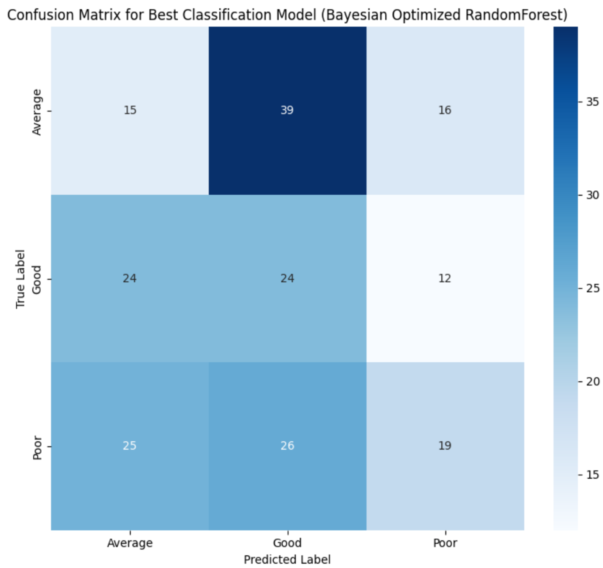
Annexure (C)

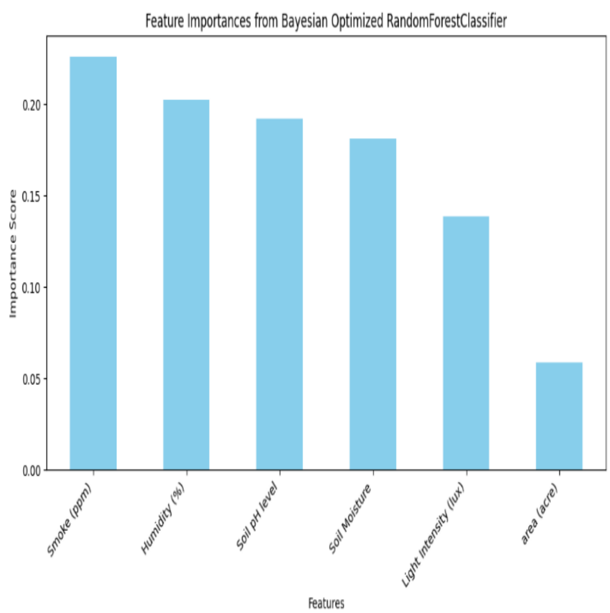
The figure shows a comparison of the different classification models on the basis of machine learning model evaluation metrics i-e F1- score, recall, precision and accuracy. The four subplots, the model ranking is similar overall, and gives output as all models are giving consistent results. The comparison shows RandomizedsearchCV-optimised Random Forest and CNN are performing better than other machine learning models, with value ranges from 0.32 to 0.33 metrics. This shows that, from all other models, two models are providing the better predictions and reducing the false positives with true class labels. The SVC provides moderate-level results, ranging from 0.30, which shows stable results but not good performance. Gradient boosting and XGBoost provide 0.29, which shows that the ensembled methods provide good classification ability through the best modelling approach in machine learning on this dataset.

The model turning effected the observation when the random forest classifier is tuned. The Random Forest gives the weakest results performance as compared to other models, with a 0.24 value, which is improved by applying the optimised version to around 0.33. In this connection, the results graphs show that hypermeters optimisation gives a very strong impact on the performance related to the prediction, and based line model is low and works as underperform if it is not well-tuned. Furthermore, in graph LSTM models, a variant of Random Forest gives results of 0.27 intermediate range value, which recommends that the very important patterns are captured, but are not as effective as the top models. In this regard, the F1 score, precision, recall and accuracy values, models are not appearing as one class biased, and classification ability is balanced. The absolute value is still low, with a value of 0.33 not exceeded by all models, which shows a clear depiction that classification models are very critical and challenging with the model design or dataset feature sets. This also shows that two important considerations first, CNN and optimised Random Forest give good and promising models among all tested models, and the second consideration is the need for improvements, which can be applied by feature engineering or adding more data, with deep model optimisation. The table gives details.

Table 2: Comparative Analysis of Machine Learning Models

Metric	**Linear Regression**	**SVM**	**Random Forest**	**Gradient Boosting**
MSE	30	70	40	50
RMSE	5	8	6	7
MAE	5	7	5	6
R-Squared	0.6	0.3	0.5	0.4
Pearson Correlation	0.8	0.8	0.7	0.7
Mean Directional Accuracy	0.7	0.6	0.65	0.65





Conclusion:

The study provides a comparative analysis of the deep learning and machine learning models. The deep learning models are used as CNN and LSTM, whereas the machine learning models are Random Forest, Gradient Boosting, and XGBoost. Comparative study provides extensive analysis of all models on the basis of F1 score, precision, recall and accuracy of the models. Further, the Random Forest model is optimised on the basis of Bayesian optimisation to improve model performance for the yield prediction. The Random Forest gives the weakest results performance as compared to other models, with a 0.24 value, which is improved by applying the optimised version to around 0.33.

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Annexure (A)

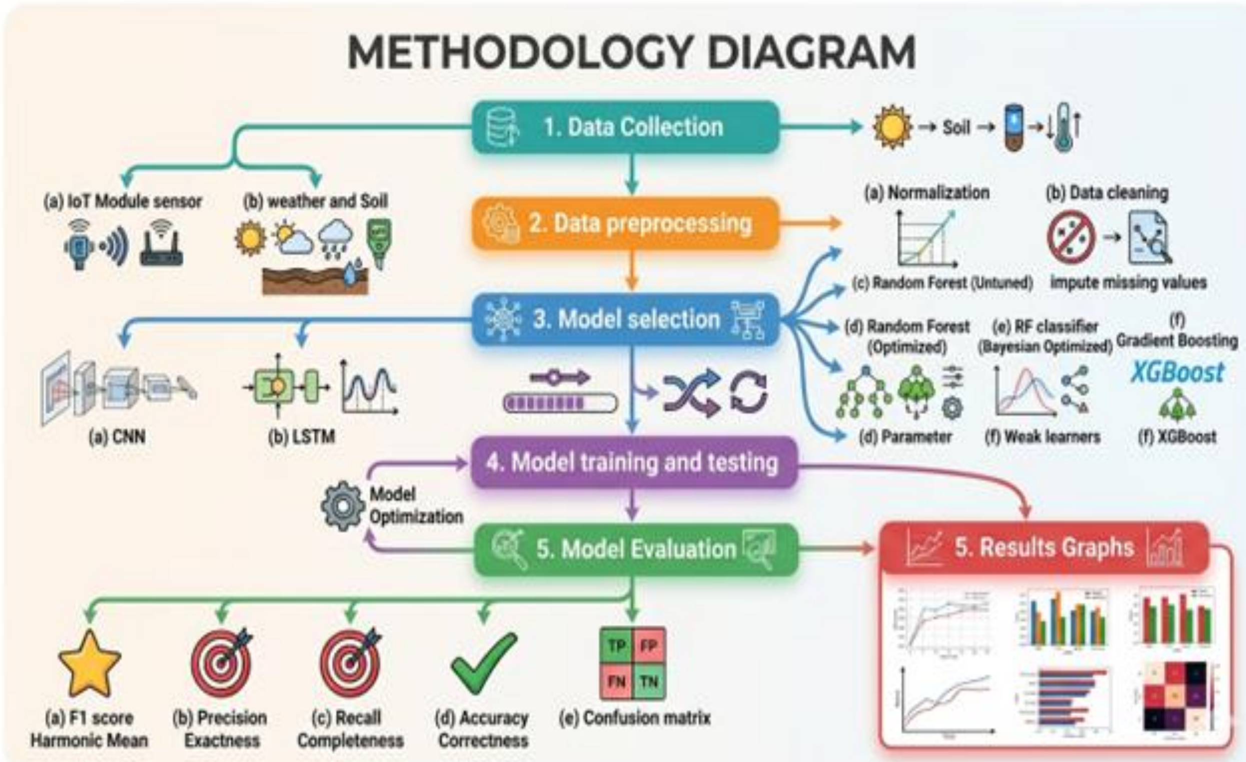

Figure 1: Methodology and work plan of the study.

Annexure (B)

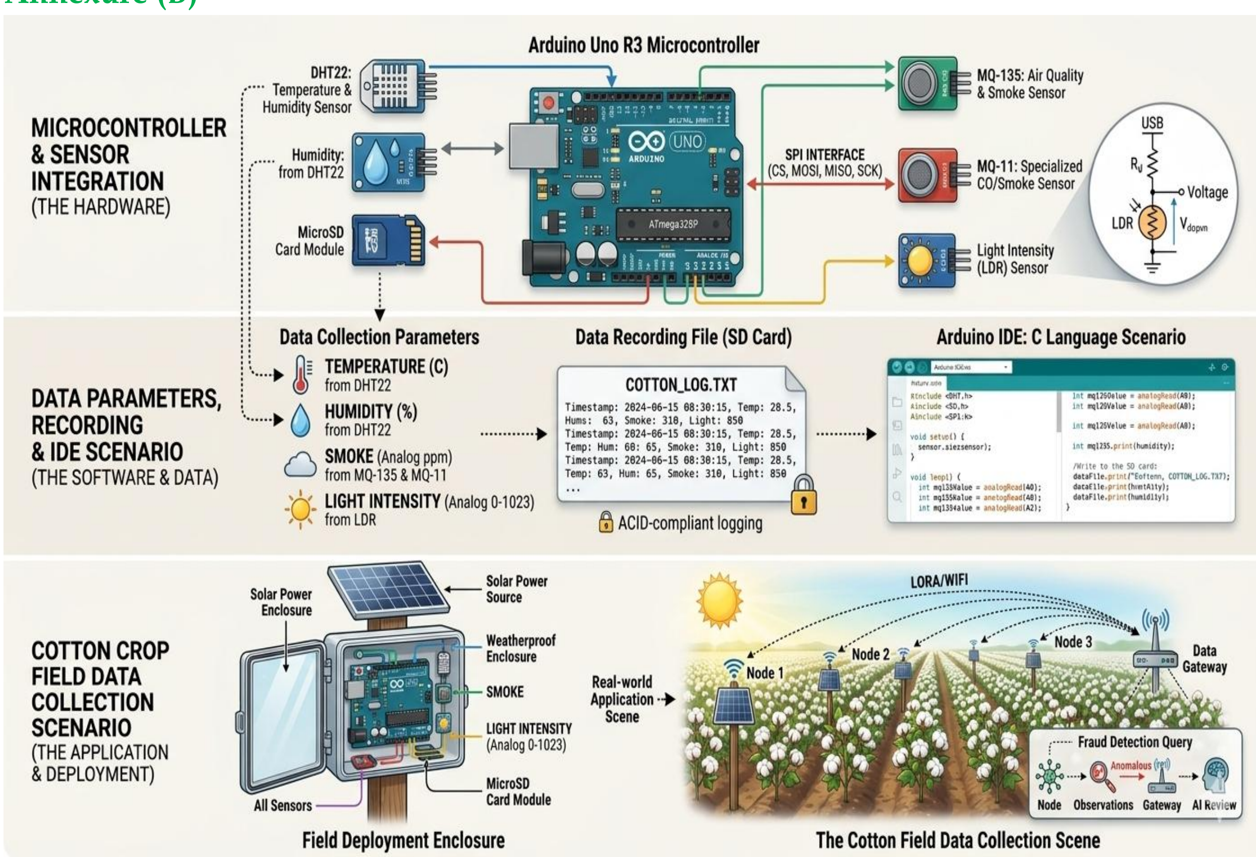

Figure 2: IoT-based Data collection process.

Annexure (C)

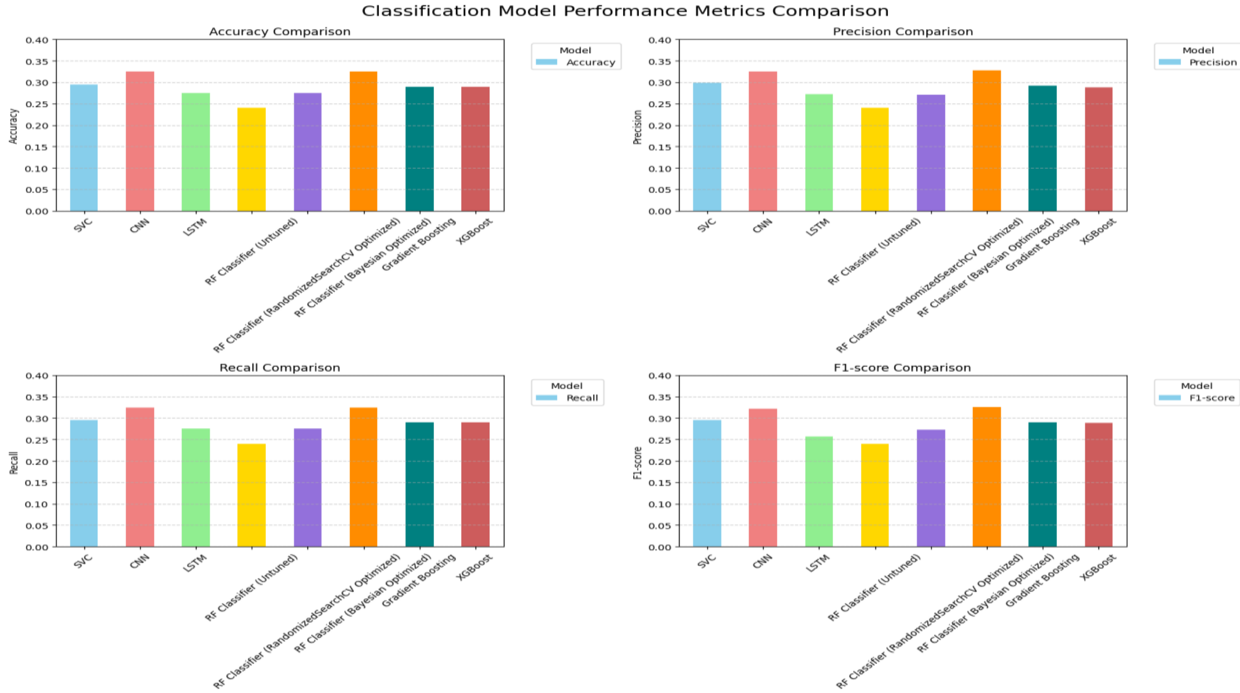

Figure 3: Classification Model Performance Comparison.