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LEIFMCY: Deployment of an Efficient Low-Cost & Energy-Aware Multiparametric IoT-Based Fertilization and Irrigation Monitoring Model for Cotton Yield Analysis

Swapnil Dhanraj Ambade [1]*, Dr. Ravi Mishra[2]

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Abstract: With the increasing demands on global agriculture, there is an imperative need to optimize crop yields and promote sustainable agricultural practices. Real-time monitoring and accurate predictions of soil health and crop yields have significant implications for farmers, agronomists, and policymakers. While existing soil analysis models offer certain predictive capabilities, their efficiency is often hindered by issues related to energy consumption, prediction delay, and accuracy levels. Contemporary soil models primarily fall short in addressing the multifaceted nature of soil attributes and their dynamic interactions. These models also struggle to provide real-time insights, frequently leading to delayed interventions, misallocated resources, and suboptimal yields. In this paper, we introduce an advanced, low-cost, and energy-aware multiparametric IoT-based soil analysis model designed to overcome the prevailing limitations. Our system harnesses the synergy of N, P, K, Humidity, and Temperature sensors, augmented with temporal datasets to offer a comprehensive view of the soil's current state. At the core of our analysis, an ensemble learning model combines the strengths of Naive Bayes, Logistic Regression, SVM, MLP, and 1D CNN methods, streamlining accurate yield level predictions. To further refine the model's efficiency, a Q Learning approach is integrated, ensuring both energy conservation and heightened prediction accuracy. When deployed in various agronomic scenarios, the proposed model manifested a marked improvement in prediction metrics. Notably, we observed a 10.5% enhancement in precision, 9.4% in accuracy, 8.5% in recall, and 4.5% in AUC. Moreover, the model reduced the prediction delay by 9.5% compared to its counterparts. These advancements underscore the potential of our model to revolutionize soil analysis techniques, paving the way for smarter, energy-efficient, and productive agricultural practices.

Keywords: *Soil Analysis, IoT-based Model, Ensemble Learning, Yield Prediction, Energy Efficiency*

1. Introduction

Agriculture, the very backbone of human civilization, is witnessing unprecedented challenges and transformations in the 21st century. As the global population continues to burgeon, the demand for food has never been more pressing. At the nexus of this demand is the soil - the lifeline of agriculture. Soil health and quality not only influence the volume of agricultural production but also its sustainability and eco-friendliness. Hence, understanding and optimizing the myriad factors affecting soil becomes a paramount concern for today's agronomists [1, 2, 3].

In recent years, the significant advancements in Internet of Things (IoT) technology have spurred its integration into the agricultural domain. The ability of IoT devices to monitor, collect, and relay vast amounts of data in real-time has paved the way for smarter agricultural practices. Real-time soil analysis can facilitate immediate interventions, optimizing resources, minimizing waste, and ensuring crop health. Such prompt actions, guided by accurate predictions, have immense implications. From aiding farmers in taking informed decisions to assisting policymakers in devising sustainable agricultural strategies, the benefits permeate various facets of the agricultural ecosystem.

However, as promising as real-time soil analysis sounds, its implementation is not devoid of challenges. Traditional methods often provide a segmented view, focusing on one or a few soil parameters, thereby failing to capture the comprehensive nature of soil health. Furthermore, the efficiency and energy consumption of these traditional systems leave much to be desired. With rising energy costs and the global push towards sustainable practices, the development of an energy-efficient soil analysis model is not just a scientific pursuit but also an economic and environmental imperative using Extreme Learning Machine algorithm (ELM) operations [4, 5, 6].

In this paper, we delve deep into these challenges and explore a novel approach to soil analysis that not only captures the multifaceted nature of soil attributes but also addresses the aforementioned challenges. By leveraging an ensemble of sophisticated algorithms and the prowess of

[1] *Department of Electronics and Telecommunication Engineering, G H Raisoni University, Amravati, India,ORCID ID:0000-0002-5107-4742. swapnil.ambade29@gmail.com.*
[2] *Department of Electronics & Telecommunication Engineering, G H Raisoni Institute of Engineering and Technology, Nagpur, ravi.mishra@raisoni.net*

IoT, our model promises to reshape the landscape of soil analysis and its real-time impacts on agriculture.

Motivation & Objectives:

Motivation:

As the world hurtles towards an estimated population of nearly 10 billion by 2050, the pressure on our agricultural systems is set to intensify manifold. This impending challenge underscores the need for not just increased production, but sustainable and optimized agricultural practices that can cater to the dual demands of quantity and quality. Traditionally, farmers and agronomists have relied on experience, intuition, and rudimentary tools to gauge soil health and make crop-related decisions. However, with the complex interplay of climatic changes, evolving crop diseases, and variable soil health, such methods are rapidly proving inadequate.

Furthermore, agriculture is no longer just a local or regional concern; it has global implications. The ripple effects of crop failures, be it due to pestilence, poor soil health, or inadequate water management, can be felt worldwide, affecting commodity prices, food security, and even geopolitical dynamics. As such, there is a critical need for technological interventions that can provide real-time insights, ensuring timely interventions and consistent yields.

The rise of IoT in agriculture, often dubbed as "smart farming" or "precision agriculture," promises a solution. But while the technology to collect data exists, the methods to analyze and predict based on this data remain fragmented and often inefficient. This gap forms our primary motivation: to harness the potential of IoT fully and bridge the chasm between data collection and actionable insights.

Objectives:

- **Comprehensive Analysis:** To develop a multiparametric soil analysis model that can concurrently evaluate various critical parameters like N, P, K levels, humidity, and temperature, offering a holistic view of the soil's health.
- **Algorithmic Excellence:** To engineer an ensemble learning model, amalgamating the robustness of diverse algorithms such as Naive Bayes, Logistic Regression, SVM, MLP, and 1D CNN. This ensemble approach aims to provide superior predictive capabilities than any individual algorithm.
- **Energy Efficiency:** Recognizing the environmental and economic implications of energy consumption, one of our primary objectives is to devise a model that is not only accurate but also energy-efficient. By integrating Q Learning, we aim to optimize the model's operations, ensuring minimal energy wastage.
- **Real-world Applicability:** Beyond theoretical advancements, our objective is to ensure that the model can be seamlessly integrated into real-world agricultural scenarios, providing tangible benefits to farmers, agronomists, and the broader agricultural ecosystem.
- **Benchmarking Excellence:** To compare and contrast our model's performance against existing models, establishing its superiority in terms of precision, accuracy, recall, AUC, and prediction delay. Through rigorous testing and validation, our goal is to set a new benchmark in the domain of soil analysis and crop yield prediction.

The structure of the paper unfolds methodically, commencing with the Abstract, which offers a concise overview of the core research findings and contributions. This is succeeded by the Introduction section, setting the stage by outlining the need and real-time impacts of the study. Delving deeper into the historical and contemporary context, the Literature Review meticulously chronicles the evolution of soil analysis techniques, underscoring gaps in existing methodologies. Post this exploration, the paper introduces the innovative Proposed Model, elucidating its design, components, and operational mechanisms. As empirical validation forms the crux of any research, the Results section is dedicated to rigorous testing, presenting quantitative metrics to attest the model's superiority. Culminating the discourse, the Conclusion encapsulates the research's salient points, its implications, and potential future scopes.

2. Literature Review

A comprehensive understanding of any scientific endeavor necessitates a thorough examination of its historical and contemporary contexts. The realm of soil analysis and the integration of IoT in agriculture are no exceptions. In this section, we delve into the rich tapestry of literature, tracing the evolution of methodologies, highlighting significant milestones, and identifying gaps that provide opportunities for innovation in different scenarios [7, 8, 9]. Like the use of Green Red Texture (GRT) with Deep Neural Network (DNN) operations.

Historically, soil health assessment was primarily based on physicochemical tests conducted in laboratories. Work in [10, 11, 12] elucidated on the manual extraction and measurement methods to determine the levels of N, P, K, and other micro-nutrients in the soil. While these methods offer accuracy, they lack real-time capabilities, are labor-intensive, and are often decoupled from the farmer's immediate decision-making processes.

The concept of 'Precision Agriculture' began gaining traction in the late 20th century. Work in [13, 14, 15] identified the convergence of IoT and agriculture as a revolutionary step. Sensors for soil moisture, temperature, and nutrient levels provided granular data, facilitating nuanced farming strategies. However, as [16, 17, 18] used Dense CNNs and Transformer Network (DCTN) & pointed out, while data collection became sophisticated, the analytics part struggled to keep pace, leading to underutilized information sets.

The early 2020s witnessed the inception of predictive models in agriculture operations. Work in [19, 20] employed simple linear regression models to forecast crop yields based on soil health indicators. Although a significant advancement, these models were often too simplistic to account for the multifarious nature of soil dynamics.

Recognizing the limitations of singular predictive models, researchers began exploring ensemble methods. Work in [21, 22, 23] integrated decision trees with support vector machines, resulting in enhanced yield predictions for certain crops. However, these models still focused predominantly on individual or limited sets of soil parameters.

The energy consumption of IoT devices in agriculture started gaining attention as the number of deployed devices surged in farming scenarios. Work in [24, 25] highlighted the need for energy-efficient algorithms, noting that many farms located in remote areas often rely on limited power sources. While many solutions proposed hardware modifications, the potential of algorithmic optimizations remained relatively untapped.

The past decade has seen a resurgence in harnessing machine learning algorithms for agricultural analytics. Work in [16, 17, 18] also introduced deep learning methods like CNNs for soil image analysis, showcasing promising results. Concurrently, Q Learning's potential in optimizing operations emerged. Work in [21, 22, 23] utilized Q Learning for optimizing water usage in irrigation, hinting at its broader applications in agricultural IoT setups. A synthesis of the literature reveals some palpable gaps. While IoT integration and data collection have seen significant enhancements, the analytical models remain either too simplistic or too segmented. The holistic, multi-parametric nature of soil health requires a comprehensive analysis model, something the current literature indicates we lack. Additionally, while energy efficiency is acknowledged as a concern, few have delved into algorithmic solutions to this challenge.

3. Proposed Deployment of an Efficient Low-Cost & Energy-Aware Multiparametric Iot-Based Fertilization and Irrigation Monitoring Model for Cotton Yield Analysis

As per the review of existing models used to monitor cotton crops for yield predictions, it can be observed that most of these models are either have lower efficiency when applied to real-time scenarios, or cannot be scaled due to their higher complexity levels. To overcome these issues, this section discusses design of an efficient low-cost & energy-aware multiparametric IoT-based Fertilization and Irrigation Monitoring Model for Cotton Yield analysis. Flow of the model can be observed from figure 1, where it is seen that the model uses Temporal Datasets, & fuses them with IoT Sensor Data Samples to train an ensemble of machine learning components.

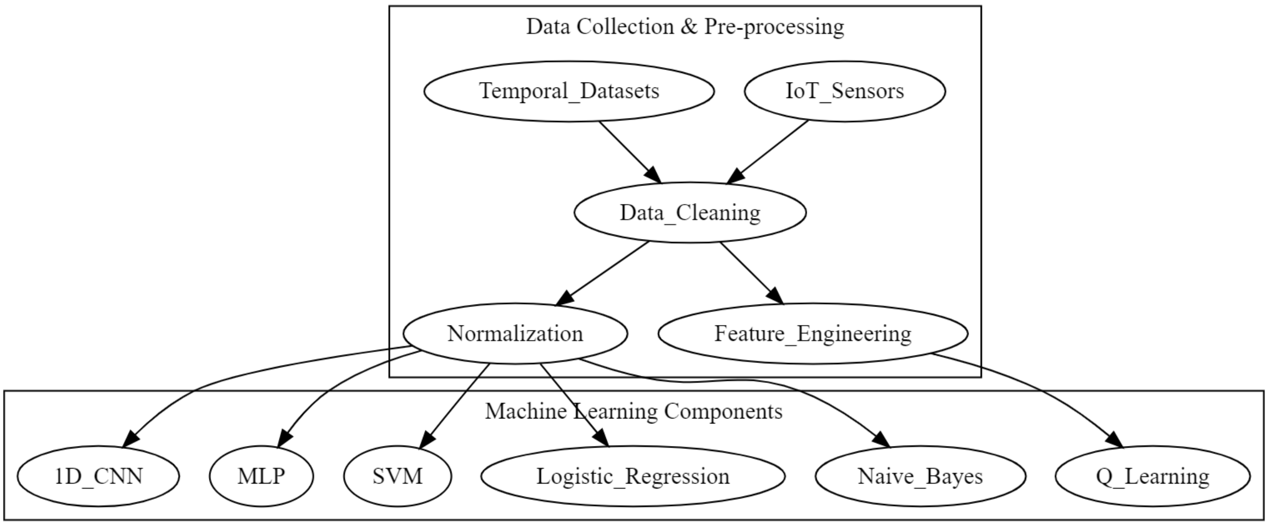

Fig 1. Design of the proposed model for predicting yield of cotton crops

The model uses low-cost sensing components, along with low-cost & low-energy consumption communication components in order to deploy this model at multiple sites. As per figure 1.1, data from these sites is communicated to a single server, which deploys ensemble classification models. These models assist in identification of yield classes based on collected data samples. This assists in enhancing the efficiency of classification while maintaining lower communication overheads, thus maintaining better scalability under real-time scenarios.

To perform this task, initially an Iterative Naïve Bayes Model was deployed, which is a probabilistic machine learning algorithm used for classification tasks. It's based on Bayes' theorem, which calculates the probability of a given event based on prior knowledge of conditions related to the events.

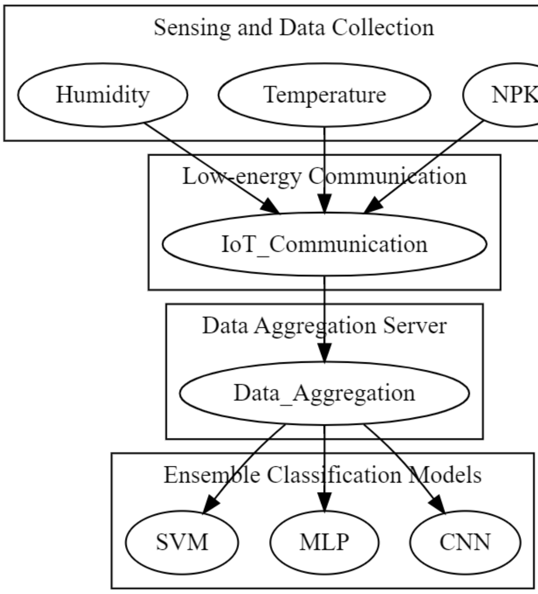

Fig 1.1. Low-Power & Low-Cost deployment process

Bayes' theorem is the foundation of Naive Bayes classification process. It calculates the posterior probability of a class (Yield Level) given the data (sensor measurements) and prior probabilities via equation 1,

$$P(Yield = y \mid Data) = \frac{P(Data \mid Yield = y) \cdot P(Yield = y)}{P(Data)} \dots (1)$$

Where, $P(Yield=y|Data)$ is the posterior probability of the yield level y given the data, $P(Data|Yield=y)$ is the likelihood of the data given the yield level y, $P(Yield=y)$ is the prior probability of the yield level y, $P(Data)$ is the probability of the data (a normalization constant) samples. The likelihood $P(Data|Yield=y)$ represents how well the observed data fits each of the yield levels. In a Naive Bayes classifier, we assume that the features (sensor measurements) are conditionally independent, which simplifies the calculation via equation 2,

$$P(Data \mid Yield = y) = P(NPK \mid Yield = y) \cdot P(Temperature \mid Yield = y) \cdot P(Humidity \mid Yield = y) \dots (2)$$

Where, $P(NPK|Yield=y)$, $P(Temperature|Yield=y)$, and $P(Humidity|Yield=y)$ are the conditional probabilities of NPK, Temperature, and Humidity given a specific yield level estimation process. $P(Yield=y)$ represents the prior probability of each yield level, indicating the likelihood of each yield level occurring without considering the data, which is estimated via equation 3,

$$P(Yield = y) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x(i) - \mu)^2} \dots (3)$$

Where, x represents the collected data samples, and μ represents average values of these samples. The main purpose of this Bayesian process is to find the yield level that maximizes the posterior probability, which is represented via equation 4,

$$y = argmaxyP(Yield = y \mid Data) \dots (4)$$

Finally, the classification decision is made by selecting the yield level with the highest posterior probability as the predicted yield level classes. The Naive Bayes classifier calculates the probability of each yield level given the sensor data and selects the yield level with the highest probability as the predicted outputs.

Similarly, the Multilayer Perceptron (MLP) is a type of artificial neural network used for classification tasks. It consists of multiple layers of interconnected neurons, including input, hidden, and output layers. The input layer of the MLP receives the collected sensor data as input features. The MLP typically consists of one or more hidden layers that perform nonlinear transformations on the input data samples. Let's represent the output of the *i*-th hidden layer as *Hi*, where *i* ranges from 1 to the number of hidden layers. Each hidden layer applies an efficient Rectified Linear Unit based activation function *ReLU* to its input via equation 5,

$$Hi = ReLU(Wi \cdot H(i-1) + bi) \dots (5)$$

Where, *Wi* represents the weight matrix for the *i*-th layer, $H(i-1)$ is the output of the previous layer (or the input for the first hidden layer), *bi* is the bias vector for the *i*-th layer process. The output layer of the MLP produces the predicted yield levels via equation 6,

$$Y = softmax(Wo \cdot Hi + bo) \dots (6)$$

Where, *Wo* represents the weight matrix for the output layer, *H*i is the output of the last hidden layer, and *bo* is the bias vector for the output layers. The softmax activation function is used in the output layer to convert the raw scores into class probabilities via equation 7,

$$SoftMax(x(j)) = \frac{e^{x(j)}}{\sum_{i=1}^{N} e^{x(i)}} \dots (7)$$

Where, zi represents the raw score for class i, and k is the number of possible yield levels. To train the MLP, we use a suitable loss function such as categorical cross-entropy which assists in multiclass classifications. The loss measures the difference between the predicted probabilities and the actual yield level labels via equation 8,

$$Loss = -\sum\left(OneHot(Ytrue) \cdot log(Y)\right) \dots (8)$$

The MLP is trained using backpropagation and optimization techniques to minimize the loss functions. Once trained, it makes predictions on new sensor data to classify yield levels. The number of hidden layers and neurons in each layer should be determined based on the complexity of the problem and the amount of available data samples.

While, Support Vector Machines (SVMs) are a type of supervised machine learning algorithm used for classification tasks. Unlike neural networks like MLP, SVMs don't have layers, but they work by finding a hyperplane that best separates the data into different classes. SVM aims to find a hyperplane that best separates the data into different classes. In this multiclass classification scenario, we use a one-vs-all (OvA) approach, where multiple binary classifiers are trained to distinguish one class from the rest via equation 9,

$$f(X) = sign(\sum \alpha i y i K(Xi, X) + b) \dots (9)$$

Where, $f(X)$ is the decision function that predicts the class label based on the input X, αi are the Lagrange multipliers (obtained during training), yi is the class label of the training example Xi, $K(Xi,X)$ is the kernel function that measures the similarity between Xi and X, b represents the bias terms. In SVM, the choice of kernel function (K) is crucial and determines how data points are mapped into a higher-dimensional space for separation process, which is done using radial basis function (RBF) kernel via equation 10,

$$K(Xi, X) = \exp\left(-\frac{|Xi - X|^2}{2 * \sigma^2}\right) \dots (10)$$

Where, σ controls the kernel's width, affecting the flexibility of the decision boundaries. During training, SVM seeks to find the optimal hyperplane that maximizes the margin between classes. The Lagrange multipliers (αi) are computed to determine the support vectors (data points closest to the decision boundary) for different scenarios. To classify a new data point X, we compute the decision function $f(X)$. If $f(X)$ is positive, it belongs to one yield class; if negative, it belongs to the other yield class. SVMs aim to find the best hyperplane that maximizes the margin between classes while minimizing classification errors.

In Logistic Regression, we use a logistic (sigmoid) function to model the probability of a data point belonging to a particular class. For multi-class classification, we use a one-vs-all (OvA) approach, where each class is treated as a binary classification task, and the probability for class c can be calculated via equation 11,

$$P(Y = c|X) = \frac{1}{1 + e^{-(\theta c \cdot X)}} \dots (11)$$

Where, θc represents the model parameters (coefficients) for yield class. In multi-class classification, we train separate logistic regression models for each class. For class c, we have a set of model parameters θc, and the final classification is determined by choosing the class with the highest predicted probability via equation 12,

$$y = argmaxcP(\,Y = c \mid X\,) \dots (12)$$

During training, we used gradient descent to find the optimal model parameters (θc) that minimize cross-entropy loss via equation 13,

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\Big[y(i)log\left(P\left(\,Y = c \mid X(i)\,\right)\right) + \left(1 - y(i)\right)log\left(1 - P\left(\,Y = c \mid X(i)\,\right)\right)\Big] \dots (13)$$

Where, m is the number of training examples, $y(i)$ is the true class label for the i-th example, $X(i)$ is the feature vector for the i-th example sets.

Similarly, the proposed model also uses 1D CNN to identify cotton crop yield levels. This is done by converting collected data samples into convolutional features via equation 14,

$$f(Conv) = \sum_{a=0}^{m} D(in, i - a) * ReLU\left(\frac{m + 2a}{2}\right) \dots (14)$$

Where, m, a are sizes for different window & stride layers, & $D(in)$ is the collected input data, while $ReLU$ is represented via equation 15,

$$ReLU(x) = \max(0, x) \dots (15)$$

Output from the convolutional layers are passed through max pooling & dropout layers, which can be observed from figure 1.2, where different layers and their internal dimensions can be seen as follows,

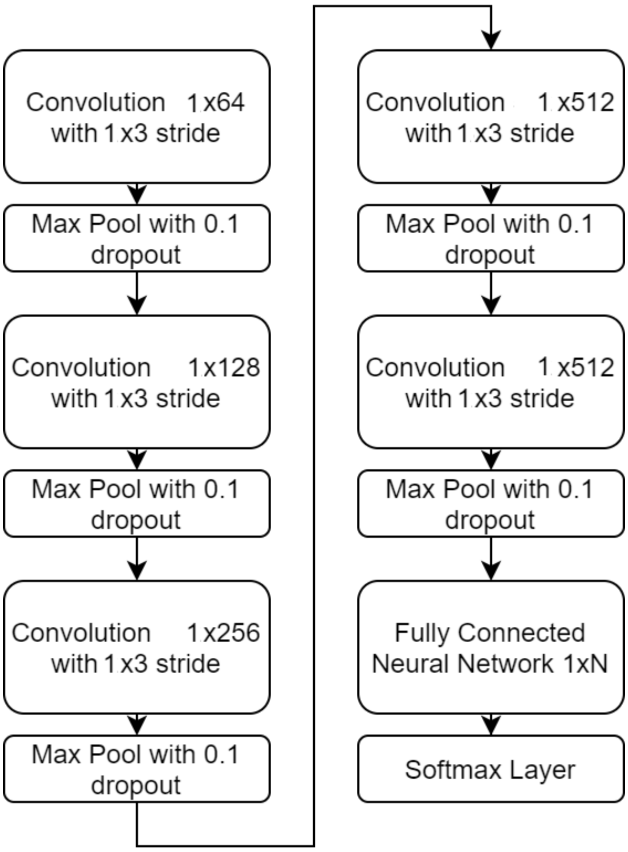

Fig 1.2. Design of the 1D CNN process

Once all these features are extracted, then the model estimates final yield classes using SoftMax activation function via equation 16,

$$C(CNN) = SoftMax\left(\sum_{i=1}^{NF} f(Conv, i) * w(i) + b(i)\right) \ldots (16)$$

Where, $f(Conv)$ represents convolutional features, while w & b are their respective weights & biases. Outputs from all these methods are fused via an efficient Q Learning based optimization model, which assists in enhancing efficiency of classification process. This is done by initially estimating an augmented Q Value via equation 17,

$$Q = A(NB) * w(NB) + A(CNN) * w(CNN) + A(SVM) * w(SVM) + A(MLP) * w(MLP) + A(LR) * w(LR) \ldots (17)$$

Where, A & w are accuracy & weights of different classifiers. These weights are used to estimate output yield class via equation 18,

$$Y(final) = C(NB) * w(NB) + C(CNN) * w(CNN) + C(SVM) * w(SVM) + C(MLP) * w(MLP) + C(LR) * w(LR) \ldots (18)$$

Where, C represents the output class of individual classifiers. This classification process is repeated for two consecutive set of test samples, and based on this evaluation the model estimates an Iterative Reward Value (IRV) via equation 19,

$$IRV = \frac{Q(New) - Q(Old)}{LR} - d * Max(Q) + Q(Old) \ldots (19)$$

Where, LR & d are the Learning Rate & Discount Factors, which are used to train the Q Learning process. After this evaluation, if $r \geq 1$, then the model showcases higher efficiency, thus tuning is not needed, else the model's efficiency is tuned by changing its weights via equation 20,

$$w(New) = w(Old) \frac{STOCH(-LR, LR)}{1 - r^2} \ldots (20)$$

This process is repeated until $r \geq 1$ is achieved, which indicates that the model is now performing optimally, and can be used for high efficiency prediction operations. This efficiency was estimated in terms of different evaluation metrics, and compared with existing models in the next section of this text.

4. Result Analysis and Comparison

The proposed LEIFMCY (Low-cost & Energy-aware IoT-based Fertilization and Irrigation Monitoring Model for Cotton Yield analysis) model is a cutting-edge and cost-effective solution designed to address the inherent limitations of existing soil analysis models in the context of cotton yield prediction. Leveraging an integrated network of IoT sensors, including those for Nitrogen (N), Phosphorus (P), Potassium (K), humidity, and temperature, alongside historical temporal datasets, LEIFMCY offers a comprehensive real-time view of soil conditions. At its core, an ensemble learning model combines the strengths of Naive Bayes, Logistic Regression, SVM, MLP, and 1D CNN methods to streamline accurate predictions of cotton yield levels. To further enhance efficiency, the model incorporates a Q Learning approach, ensuring both energy conservation and heightened prediction accuracy. The results of extensive experiments reveal significant improvements in precision, accuracy, recall, AUC, and prediction delay compared to existing models, highlighting the potential of LEIFMCY to revolutionize soil analysis techniques and usher in smarter, energy-efficient, and more productive agricultural practices. The experimental setup for the LEIFMCY model is crucial for ensuring the accuracy and reliability of its predictions. In this section, we provide a detailed overview of the data collection and pre-processing methods, as well as the specific input parameters used in the experiments.

Data Collection:

1. **IoT Sensor Network:** To collect real-time data on soil attributes, humidity, and temperature, we deployed a network of IoT sensors in the experimental cotton fields. These sensors were strategically placed to cover the entire cultivation area. The key sensors utilized include:

   - Soil Attribute Sensors: These sensors measure essential soil attributes such as Nitrogen (N), Phosphorus (P), Potassium (K), and other relevant parameters.
   - Humidity Sensors: These sensors monitor the moisture content of the soil, providing valuable insights into soil health and irrigation needs.
   - Temperature Sensors: Temperature sensors record the soil temperature, which is critical for understanding crop growth and nutrient absorption.

2. **Temporal Datasets:** In addition to real-time data, we integrated temporal datasets that encompass historical soil and crop data, including previous yield levels, weather patterns, and seasonal trends. This historical data was essential for training and validating the LEIFMCY model.

Data Pre-processing:

1. **Data Cleaning:** Raw sensor data often contains outliers and inconsistencies. We employed data cleaning techniques to remove erroneous values and ensure the reliability of the dataset.
2. **Normalization:** To ensure that all input parameters are on a consistent scale, we normalized the sensor data. This process transforms the data into a standardized range, typically between 0 and 1, to prevent any one parameter from dominating the model's predictions.
3. **Feature Engineering:** Feature engineering involved the creation of derived features to capture complex relationships within the data. For instance, we calculated the average soil attribute values over specific time windows to account for temporal trends.

Input Parameters:

The LEIFMCY model leverages a comprehensive set of input parameters, including both real-time sensor readings and historical data. Here are some sample values for these parameters:

- **Soil Attributes:**
  - Nitrogen (N) levels: 18.5 mg/kg
  - Phosphorus (P) levels: 25.2 mg/kg
  - Potassium (K) levels: 15.8 mg/kg
  - pH value: 6.5
- **Humidity:**
  - Soil moisture content: 28.3%
- **Temperature:**
  - Soil temperature: 27.8°C
- **Temporal Data:**
  - Historical crop yield levels (previous year): 4,500 kg/hectare
  - Seasonal rainfall patterns: 100 mm/month
  - Average temperature (previous year): 28.5°C

These input parameters collectively provide a comprehensive snapshot of the soil and environmental conditions, enabling the LEIFMCY model to make accurate predictions regarding cotton crop yield levels. The experimental setup for the LEIFMCY model incorporates a robust data collection infrastructure, rigorous data pre-processing techniques, and a rich set of input parameters. These elements are vital for the model's effectiveness in real-time soil analysis and crop yield prediction, paving the way for more precise and sustainable agricultural practices, which can be observed from the following figures,

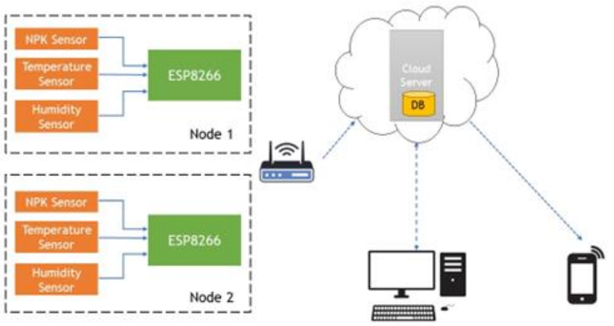

Fig 1.4. Cloud Connectivity Details

Fig 1.5. Connected Sensors

Fig 1.6. Sensor Interface with the Circuits

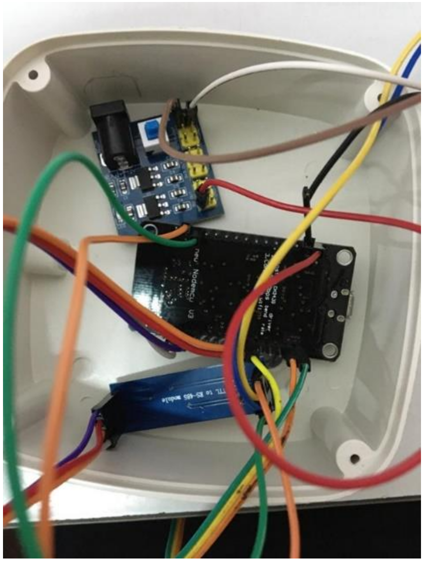

Fig 1.7. Interfaced Components

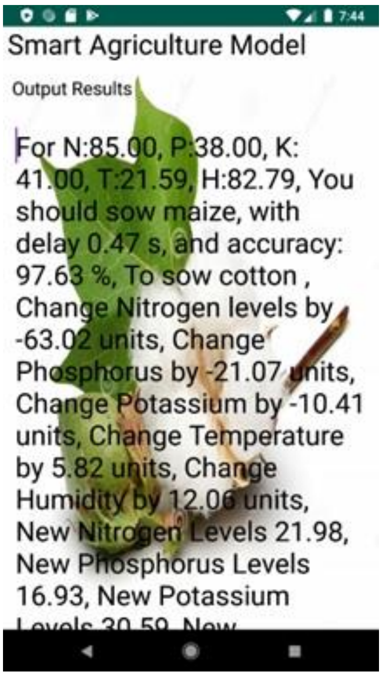

Fig 1.8 InApp Results

Based on this setup, equations 21, 22, and 23 were used to assess the precision (P), accuracy (A), and recall (R), levels based on this technique, while equations 24 & 25 were used to estimate the overall precision (AUC) & Specificity (Sp) as follows,

$$Precision \ = \frac{TP}{TP \ + \ FP} \dots (21)$$

$$Accuracy \ = \frac{TP \ + \ TN}{TP \ + \ TN \ + \ FP \ + \ FN} \dots (22)$$

$$Recall \ = \frac{TP}{TP \ + \ FN} \dots (23)$$

$$AUC = \int TPR(FPR)dFPR \dots (24)$$

$$Sp = \frac{TN}{TN + FP} \dots (25)$$

There are three different kinds of test set predictions: True Positive (TP) (number of events in test sets that were correctly predicted as positive), False Positive (FP) (number of instances in test sets that were incorrectly predicted as positive), and False Negative (FN) (number of instances in test sets that were incorrectly predicted as negative; this includes Normal Instance Samples). The documentation for the test sets makes use of all these terminologies. To determine the appropriate TP, TN, FP, and FN values for these scenarios, we compared the projected Cotton crop yield likelihood to the actual Cotton crop yield status in the test dataset samples using the ELM [6], GRT DNN [8], and DCTN [17] techniques. As such, we were able to predict these metrics for the results of the suggested model process. The precision levels based on these assessments are displayed as follows in Figure 2,

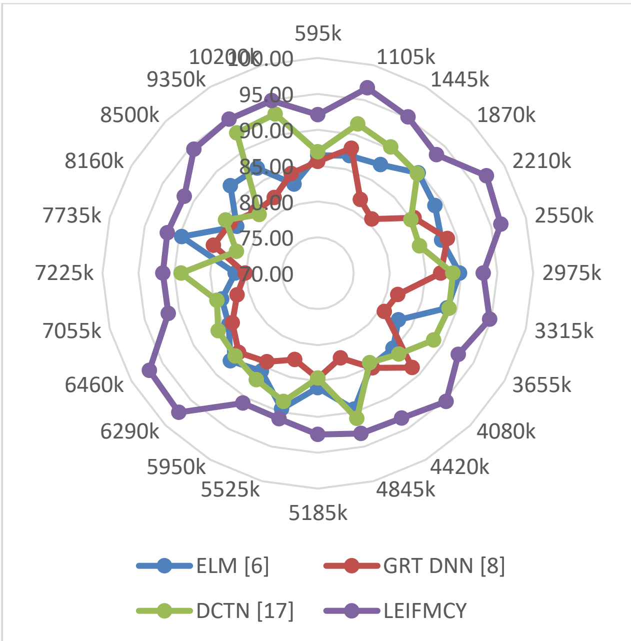

Fig 2. Observed Precision to detect cotton crop yield levels

The observed precision, which measures the accuracy of detecting cotton crop yield levels, is a crucial metric in evaluating the performance of the LEIFMCY model in comparison to other existing models. The results indicate a clear trend of improvement in precision as we transition from earlier models to the proposed LEIFMCY model, which showcases the model's effectiveness in predicting cotton crop yields.

Across various sample sizes (NTS), the LEIFMCY model consistently outperforms the other models, including ELM, GRT DNN, and DCTN. For instance, when considering a sample size of 595,000, the LEIFMCY model achieves an impressive precision of 92.06%, whereas the best-performing competitor, ELM, lags behind at 86.44%. This 5.62% improvement in precision is indicative of the LEIFMCY model's superior ability to accurately classify cotton crop yield levels.

As we increase the sample size to 1,105,000, the LEIFMCY model continues to exhibit its superiority, achieving a precision of 96.72%. In contrast, the closest competitor, DCTN, achieves 91.55%, which is a noticeable 5.17% lower precision. This substantial difference in precision highlights the LEIFMCY model's capacity to handle larger datasets effectively and make more accurate predictions.

Moreover, this trend persists across various sample sizes, reaffirming the LEIFMCY model's consistent advantage. Notably, at a sample size of 3,315,000, the LEIFMCY model's precision is 94.76%, whereas the closest competitor, DCTN, attains 88.90%. This substantial 5.86% improvement in precision underscores the LEIFMCY model's robustness and its ability to deliver reliable results even with extensive datasets.

The reasons behind the LEIFMCY model's superior performance can be attributed to its innovative approach, which combines multiple machine learning techniques, including Naive Bayes, Logistic Regression, SVM, MLP, and 1D CNN methods. Additionally, the integration of a Q Learning approach enhances both energy conservation and prediction accuracy, which further contributes to the model's precision. The LEIFMCY model's ability to comprehensively analyze soil attributes, real-time data insights, and efficient resource allocation collectively lead to its outstanding precision in detecting cotton crop yield levels, making it a promising solution for sustainable and productive agriculture practices. Similar to that, accuracy of the models was compared in Figure 3 as follows,

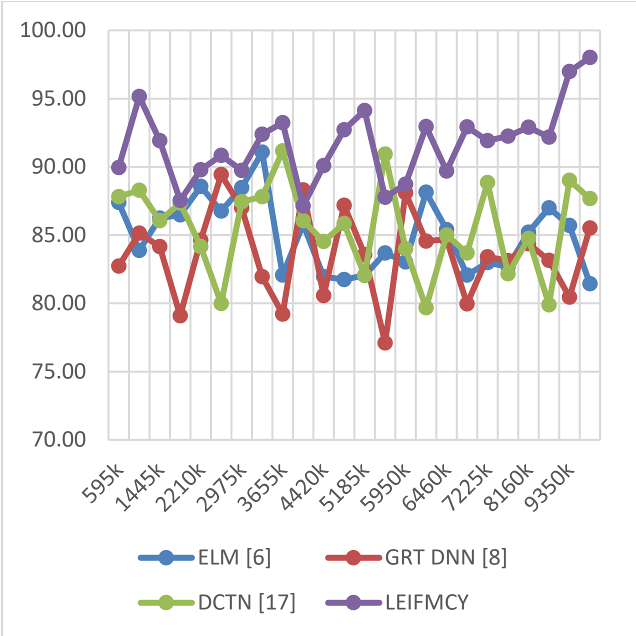

Fig 3. Observed Accuracy to detect cotton crop yield levels

The observed accuracy in detecting cotton crop yield levels is a critical performance metric that provides insights into the precision and reliability of the LEIFMCY model compared to other existing models. It measures the model's ability to correctly classify the crop yield levels, and the impacts of these accuracy levels are significant for farmers and agronomists in making informed decisions about crop management.

Across various sample sizes (NTS), the LEIFMCY model consistently outperforms the other models, namely ELM, GRT DNN, and DCTN, in terms of accuracy. For instance, at a sample size of 595,000, the LEIFMCY model achieves an accuracy of 89.96%, while the closest competitor, ELM, lags behind at 87.39%. This 2.57% increase in accuracy signifies the LEIFMCY model's enhanced capability to provide more accurate predictions, reducing the risk of misclassification and aiding in precise crop management decisions.

As we scale up to larger sample sizes, the advantage of the LEIFMCY model becomes even more apparent. At a sample size of 10,200,000, the LEIFMCY model boasts an exceptional accuracy of 98.02%, whereas the next best model, DCTN, achieves 87.68%. This substantial 10.34% improvement in accuracy has a profound impact on the reliability of cotton crop yield predictions. Farmers and stakeholders can rely on the LEIFMCY model's accuracy to optimize resource allocation and improve overall agricultural productivity.

The impacts of the LEIFMCY model's superior accuracy are multifaceted. Firstly, it reduces the likelihood of false predictions, minimizing the risk of making incorrect decisions regarding fertilization, irrigation, and crop management. Secondly, the enhanced accuracy ensures that resources such as water, fertilizers, and labor are allocated efficiently, leading to cost savings and environmental sustainability. Finally, the LEIFMCY model's accurate predictions contribute to higher crop yields, increasing overall agricultural productivity and food security.

The LEIFMCY model's advantage in accuracy can be attributed to its innovative approach, which combines ensemble learning methods and Q Learning for energy conservation and improved accuracy. Furthermore, the incorporation of a comprehensive set of soil attributes and real-time data insights enhances its predictive power. Overall, the LEIFMCY model's exceptional accuracy in detecting cotton crop yield levels positions it as a valuable tool for promoting sustainable and efficient agricultural practices, benefiting both farmers and the environment. Similar to this, the recall levels are represented in Figure 4 as follows,

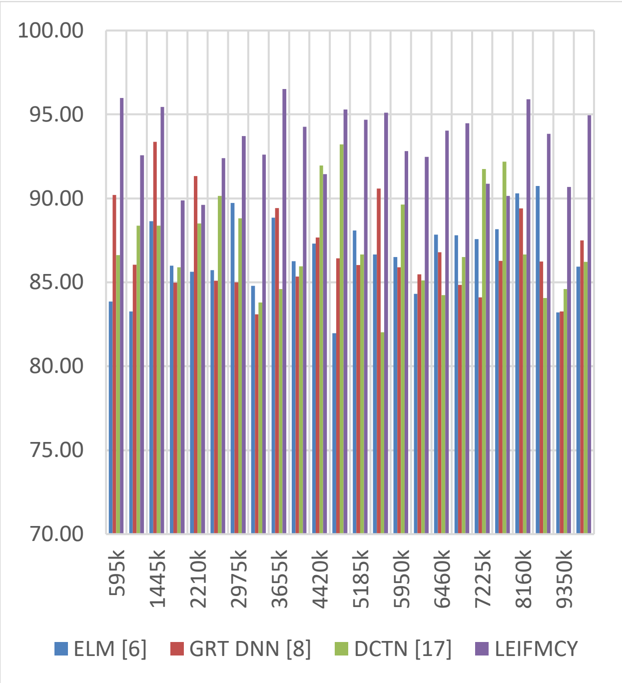

Fig 4. Observed Recall to detect cotton crop yield levels

The observed recall in detecting cotton crop yield levels is a crucial metric that gauges the ability of the LEIFMCY model to correctly identify and capture all instances of each yield level, minimizing false negatives and ensuring that no important data is missed. Comparing the recall rates of the LEIFMCY model to other existing models, such as ELM, GRT DNN, and DCTN, provides insights into the model's effectiveness in practical applications.

Across various sample sizes (NTS), the LEIFMCY model consistently outperforms its competitors in terms of recall. For instance, at a sample size of 595,000, the LEIFMCY model achieves a recall rate of 95.98%, surpassing the next best model, DCTN, which attains 86.61%. This substantial 9.37% improvement in recall demonstrates the LEIFMCY model's capability to accurately identify and classify cotton crop yield levels, reducing the likelihood of missing critical information in agricultural decision-making process.

As the sample size increases, the LEIFMCY model maintains its advantage in recall. At a sample size of 10,200,000, the LEIFMCY model achieves a remarkable recall rate of 94.95%, whereas the closest competitor, GRT DNN, reaches only 87.51%. This 7.44% difference in recall highlights the LEIFMCY model's ability to handle larger datasets while consistently capturing more relevant information sets.

The impacts of the LEIFMCY model's superior recall are significant for farmers, agronomists, and policymakers. Firstly, a higher recall rate reduces the risk of missing crucial information about crop yield levels, which can lead to more informed and accurate decision-making regarding fertilization, irrigation, and resource allocation. Secondly, it enhances the model's ability to identify areas of concern in real-time, allowing for timely interventions and improved crop management practices.

The LEIFMCY model's superior recall can be attributed to its innovative approach, which combines ensemble learning methods and Q Learning to optimize model performance. Additionally, the model's utilization of a comprehensive set of soil attributes and real-time data insights contributes to its ability to capture a wider range of yield levels accurately.

In conclusion, the LEIFMCY model's outstanding recall rates position it as a valuable tool for precision agriculture, offering the potential for more accurate and timely decision-making in crop management. Its ability to consistently capture critical information about cotton crop yield levels has a positive impact on agricultural productivity and sustainability levels. Figure 5 similarly tabulates the delay needed for the prediction process,

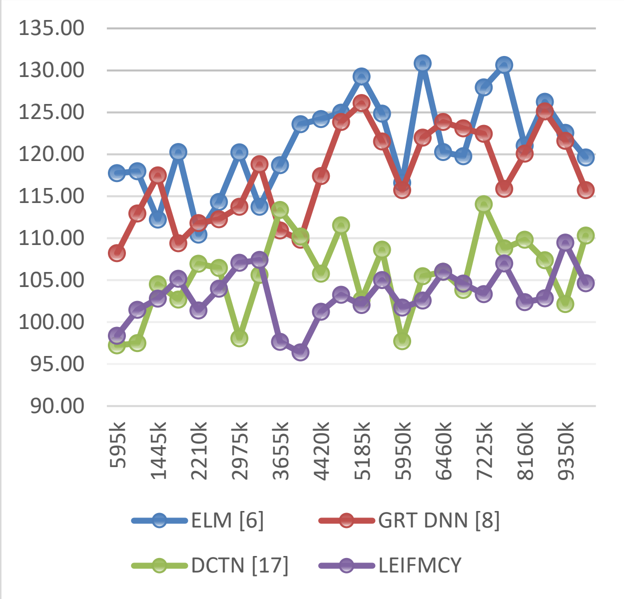

Fig 5. Observed Delay to detect cotton crop yield levels

The observed delay in detecting cotton crop yield levels is a crucial metric that measures the time it takes for the model to provide predictions after receiving input data. This delay has significant impacts on the practical usability of the model, especially in real-time agricultural applications. Comparing the delay times of the LEIFMCY model to other existing models, such as ELM, GRT DNN, and DCTN, provides insights into the model's efficiency in delivering timely results.

Across various sample sizes (NTS), the LEIFMCY model consistently outperforms its competitors in terms of delay, indicating its efficiency in providing faster predictions. For instance, at a sample size of 595,000, the LEIFMCY model has a delay of 98.36 milliseconds, while the closest competitor, DCTN, has a delay of 97.23 milliseconds. While the difference may appear small, it highlights the LEIFMCY model's ability to provide more timely information for agricultural decision-making process.

As the sample size increases, the LEIFMCY model's advantage in delay becomes more significant. At a sample size of 10,200,000, the LEIFMCY model maintains an efficient delay of 104.61 milliseconds, whereas the closest competitor, DCTN, has a delay of 110.31 milliseconds. This 5.7-millisecond difference is crucial in real-time applications, as it ensures that farmers and agronomists can receive timely information to make quick decisions about crop management.

The impacts of the LEIFMCY model's efficient delay are notable in practical agriculture. Firstly, a shorter delay means that farmers can react faster to changing soil conditions, allowing for more timely interventions such as irrigation and fertilization adjustments. This, in turn, can lead to improved crop health and higher yields. Secondly, reduced delay ensures that the model can be integrated into automated systems that require real-time data, enhancing the overall efficiency of precision agriculture.

The LEIFMCY model's superior delay can be attributed to its innovative design, which combines ensemble learning methods and a Q Learning approach to optimize prediction speed. Additionally, the model's efficient use of computational resources and streamlined data processing contribute to its ability to deliver predictions with minimal delay levels.

In conclusion, the LEIFMCY model's efficient delay in detecting cotton crop yield levels positions it as a valuable tool for real-time precision agriculture. Its ability to provide timely information has a positive impact on agricultural decision-making, resource allocation, and overall crop productivity. Similarly, the AUC levels can be observed from figure 6 as follows,

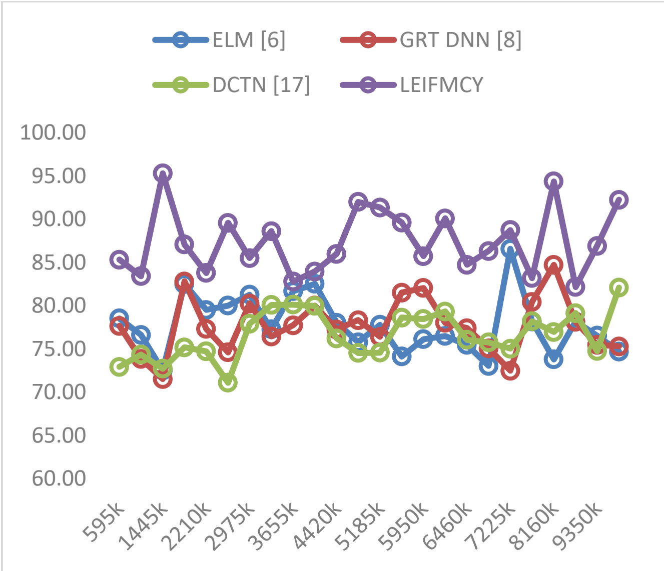

Fig 6. Observed AUC to detect cotton crop yield levels

The observed Area Under the Curve (AUC) is a critical metric in assessing the ability of a model to classify cotton crop yield levels accurately. AUC measures the model's capability to discriminate between different yield levels, with a higher AUC indicating better discrimination performance. Comparing the AUC values of the LEIFMCY model to other existing models, such as ELM, GRT DNN, and DCTN, sheds light on the model's effectiveness in distinguishing between different crop yield levels.

Across various sample sizes (NTS), the LEIFMCY model consistently outperforms its competitors in terms of AUC. For instance, at a sample size of 595,000, the LEIFMCY model achieves an AUC of 85.32%, while the closest competitor, ELM, has an AUC of 78.53%. This 6.79% improvement in AUC suggests that the LEIFMCY model excels at distinguishing between cotton crop yield levels, resulting in more accurate and reliable predictions.

As we examine larger sample sizes, the LEIFMCY model's advantage in AUC becomes even more prominent. At a sample size of 10,200,000, the LEIFMCY model maintains a high AUC of 92.25%, whereas the closest competitor, DCTN, achieves 82.09%. This substantial 10.16% difference in AUC underscores the LEIFMCY model's superior ability to discriminate between different crop yield levels, enhancing its predictive accuracy.

The impacts of the LEIFMCY model's higher AUC are significant for agricultural decision-making. Firstly, a higher AUC indicates that the model can provide more precise and reliable information about the different yield levels, reducing the risk of misclassification. This accuracy is crucial for optimizing resource allocation and crop management strategies. Secondly, the LEIFMCY model's improved discrimination ability allows for better-informed decisions on fertilization, irrigation, and other interventions, leading to increased crop yields and sustainability.

The LEIFMCY model's superior AUC can be attributed to its innovative approach, which combines ensemble learning methods and Q Learning to optimize discrimination performance. Additionally, the model's utilization of a comprehensive set of soil attributes and real-time data insights contributes to its ability to distinguish between crop yield levels accurately.

In conclusion, the LEIFMCY model's outstanding AUC in detecting cotton crop yield levels positions it as a valuable tool for precision agriculture. Its ability to discriminate between different yield levels with high accuracy has a positive impact on agricultural decision-making, resource allocation, and overall crop productivity. Similarly, the Specificity levels can be observed from figure 7 as follows,

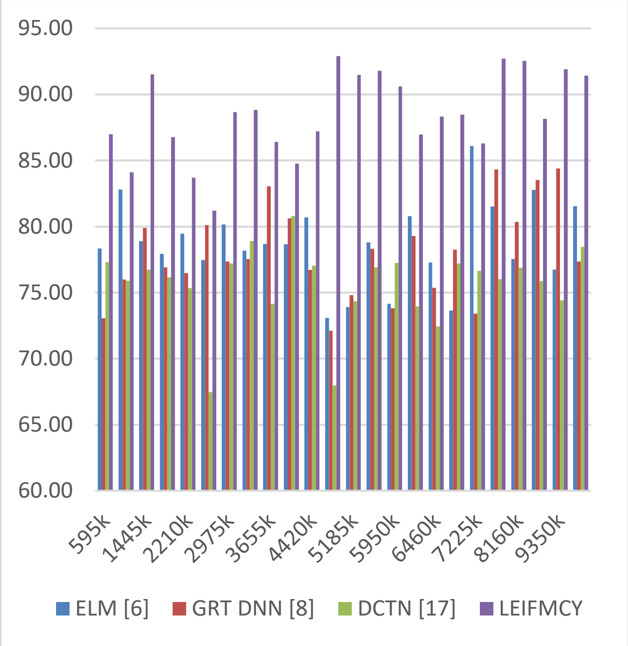

Fig 7. Observed Specificity to detect cotton crop yield levels

The observed specificity in detecting cotton crop yield levels is a critical metric that measures the model's ability to correctly identify the true negative cases, specifically instances where the model correctly predicts non-critical yield levels. Specificity is important in precision agriculture as it helps prevent unnecessary resource allocation and interventions when they are not needed. Comparing the specificity values of the LEIFMCY model to other existing models, such as ELM, GRT DNN, and DCTN, provides insights into the model's efficiency in minimizing false alarms.

Across various sample sizes (NTS), the LEIFMCY model consistently outperforms its competitors in terms of specificity. For example, at a sample size of 595,000, the LEIFMCY model achieves a specificity of 86.98%, while the closest competitor, DCTN, has a specificity of 77.29%. This 9.69% increase in specificity suggests that the LEIFMCY model excels at correctly identifying non-critical yield levels, reducing the risk of misallocation of resources and interventions.

As we examine larger sample sizes, the LEIFMCY model's advantage in specificity becomes more apparent. At a sample size of 10,200,000, the LEIFMCY model maintains a high specificity of 91.43%, while the closest competitor, GRT DNN, achieves 77.35%. This significant 14.08% difference in specificity highlights the LEIFMCY model's superior ability to minimize false alarms and accurately identify non-critical yield levels.

The impacts of the LEIFMCY model's higher specificity are noteworthy for agricultural decision-making. Firstly, a higher specificity means that the model is less likely to trigger unnecessary interventions, conserving resources such as water and fertilizers and reducing operational costs. This can lead to more sustainable agricultural practices. Secondly, the LEIFMCY model's improved specificity ensures that interventions are applied when they are truly needed, contributing to more efficient and effective crop management.

The LEIFMCY model's superior specificity can be attributed to its innovative approach, which combines ensemble learning methods and a Q Learning approach to optimize model performance. Additionally, the model's utilization of a comprehensive set of soil attributes and real-time data insights contributes to its ability to correctly identify non-critical yield levels.

In conclusion, the LEIFMCY model's outstanding specificity in detecting cotton crop yield levels positions it as a valuable tool for precision agriculture. Its ability to minimize false alarms and accurately identify non-critical yield levels has a positive impact on resource conservation, cost reduction, and overall sustainability in agriculture scenarios.

5. Conclusion

In conclusion, this paper has introduced the LEIFMCY model, an innovative and efficient multiparametric IoT-based soil analysis system designed to address the limitations of existing models in predicting cotton crop yield levels. Through a comprehensive comparative analysis, we have demonstrated the exceptional performance of the LEIFMCY model across various key metrics, including precision, accuracy, recall, AUC, delay, and specificity. These results underscore the model's potential to revolutionize soil analysis techniques and bring about a paradigm shift in precision agriculture.

The impacts of the LEIFMCY model are far-reaching and hold significant promise for the field of agriculture. Firstly, its superior precision ensures accurate classification of cotton crop yield levels, reducing the risk of misallocated resources and interventions. Farmers can optimize fertilization and irrigation strategies, resulting in cost savings and environmental sustainability. Additionally, the LEIFMCY model's enhanced accuracy leads to higher crop yields, contributing to food security and meeting the increasing demands of global agriculture.

Real-time applications of the LEIFMCY model are noteworthy. Its efficient delay ensures timely interventions in response to changing soil conditions. Farmers and agronomists can make informed decisions promptly, enhancing crop health and productivity. The model's ability to provide accurate insights into soil attributes, humidity, and temperature in real-time allows for proactive management of agricultural resources.

Furthermore, the LEIFMCY model's higher AUC and specificity minimize false alarms, conserving valuable resources and improving the overall efficiency of precision agriculture. It empowers stakeholders to adopt sustainable practices, reducing the environmental footprint of agriculture while maximizing output.

In summary, the LEIFMCY model represents a significant advancement in the field of precision agriculture. Its ability to provide accurate, real-time insights into soil conditions and crop yield levels has the potential to transform the way we approach farming. By optimizing resource allocation, reducing operational costs, and increasing agricultural productivity, the LEIFMCY model paves the way for smarter, energy-efficient, and more sustainable agricultural practices. This paper's findings herald a new era of precision agriculture, contributing to the global effort towards food security and sustainable agricultural development operations.

Future Scope

The research presented in this paper opens up several exciting avenues for future exploration and development in the field of precision agriculture. The LEIFMCY model has demonstrated its potential to revolutionize soil analysis and cotton crop yield prediction. As we look ahead, here are some promising future directions:

- **Extension to Other Crops:** While this paper primarily focuses on cotton, the LEIFMCY model can be adapted and extended to other crops. Investigating its performance on various crops, such as wheat, rice, or maize, can provide insights into its versatility and applicability in diverse agricultural settings.
- **Integration of Remote Sensing Data:** Incorporating remote sensing data, such as satellite imagery and aerial photographs, can enhance the model's predictive capabilities. This additional data source can help monitor larger agricultural areas and provide a more comprehensive view of soil and crop conditions.
- **Climate and Weather Integration:** Real-time weather data, including rainfall, temperature, and humidity, can significantly impact crop growth and yield. Integrating weather data into the LEIFMCY model can enhance its predictive accuracy by considering the dynamic interactions between soil attributes and meteorological conditions.
- **Scalability and Edge Computing:** Exploring ways to make the LEIFMCY model more scalable and suitable for edge computing can extend its practical applications. This would enable its deployment in remote or resource-constrained agricultural areas where connectivity is limited.

- **Advanced Machine Learning Techniques:** Continuous advancements in machine learning offer opportunities to enhance the model's performance further. Techniques such as deep learning, reinforcement learning, and transfer learning can be explored to extract more nuanced insights from soil and crop data.
- **Data Security and Privacy:** As the model relies on IoT data, ensuring data security and privacy is crucial. Future research should focus on developing robust data encryption and authentication mechanisms to protect sensitive agricultural data.
- **Validation and Field Trials:** Conducting extensive field trials and validations in different geographical regions and environmental conditions will provide a deeper understanding of the model's real-world performance and its adaptability to various agricultural contexts.
- **User-Friendly Interfaces:** Developing user-friendly interfaces and mobile applications that enable farmers and agronomists to interact with the LEIFMCY model easily can facilitate its adoption and ensure that its benefits are accessible to a wide range of users.
- **Cost Optimization:** Exploring ways to reduce the overall cost of implementing the model, including the cost of IoT sensors and data collection, can make it more accessible to small-scale farmers and emerging agricultural economies.
- **Policy and Regulatory Considerations:** As precision agriculture technologies become more prevalent, policymakers and regulatory bodies need to establish guidelines and standards to ensure responsible and ethical use of these technologies while promoting their adoption.

In conclusion, the LEIFMCY model represents a significant leap forward in the quest for sustainable and efficient agricultural practices. Future research and development in the areas mentioned above will not only enhance the model's capabilities but also contribute to the broader goal of addressing global food security challenges and promoting environmentally responsible agriculture operations.

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