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An AI-Based Approach in Precision Agriculture for Crop Yield Prediction

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ABSTRACT
The Artificial Intelligence and Internet of Things (IoT) technologies enable real-time processing of agriculture sensor data, supporting rapid, automated, and data-driven decision-making in smart farming systems. IoT devices continuously capture soil characteristics, weather conditions (temperature, humidity, rainfall), crop health metrics (NDVI, Chlorophyll levels via drones), and livestock activity. Hourly mean values and inter-parameter relationships are computed to predict crop yield classes (low, medium, high). The model performance is assessed using classification accuracy and permutation feature importance, which quantifies the impact of each variable by measuring accuracy degradation when features are randomly shuffled. Time-series comparisons between predicted and actual yield classes reveal that transitional weather periods. The weather periods, such as sudden heat spikes or moisture shifts, introduce greater volatility and increase prediction difficulty. Training, validation accuracy, and loss curves epochs are analyzed to evaluate learning behavior and detect overfitting. Training accuracy improves steadily with more epochs, while validation accuracy begins lower as the model gradually adapts to generalize effectively to unseen data.

Keywords: IoT; Machine Learning; Smart agriculture; Weather and soil data

1. INTRODUCTION

The rapid expansion of Internet of Things (IoT) technologies and recent advances in artificial intelligence (AI) have transformed data-driven applications across multiple sectors, including agriculture [1]. Smart agriculture system now leverages distributed sensors, unmanned aerial vehicles, and automated monitoring devices to collect high-resolution data on soil conditions, weather dynamics, crop health, and livestock activity [2]. While these technologies generate rich streams of real-time information, their full potential remains underutilized due to limited integration with predictive AI models capable of converting raw data into actionable insights. As a result, many farming operations still relay on manual assessments, delayed responses, and conventional yield estimation methods that cannot adequately capture rapid environmental fluctuations. Despite the availability of continuous sensor data, existing yield prediction models often fail to incorporate real-time, multi-modal inputs and struggle to maintain accuracy during periods of environmental volatility. These limitations hinder timely decision-making in precision agriculture, reducing efficiency and resilience in crop management. The IIoT [3] and manufacturing provides not only predictive maintained operations but also provides the quality control with help of AI-powered cameras inspect products in real time for defects. The smart homes and consumer IoT [4] such as voice assistant provide AI-driven devices like Alexa or Google Home control IoT – Enable appliances. This leads not only the connected devices but also focuses on the energy optimization [5] with smart thermostats learn user behavior to adjust heating/cooling efficiently. Another important application is supplying chain activities like smart inventory management with the help of IoT sensors track stock levels, and AI predicts demand to prevent shortages. The personalized shopping [4] provides many activities which can be analyzed by using AI techniques. The activities such as customer behavior, retail prices increase and decrease, likeness and dislikes can be monitored by using AI techniques.

1.1. IoT and Smart Agriculture

The benefits of AI and IoT based systems are very magical which includes the real-time decision making in which AI process IoT data instantly for faster response [6]. The integration of IoT (Internet of things) with smart agriculture [7] enables real-time monitoring [8], automation [9], and data driven decision-making more efficient, sustainable, and less labor-intensive. The IoT sensors collects soil conditions, weather parameters like temperature, humidity, rainfall, crop health (NDVI, chlorophyll levels via drones), and livestock activities are easy to management and control up to date. The more advance techniques like drones and satellite image sensory [10] includes the multispectral drones and AI – powered image analysis. These techniques are used for the capture crop health [11], and detect pests [12], disease and growth patterns [13]. IoT (internet of things) in agriculture [14] refers to the use of interconnected sensors, devices,

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and machines to monitor and automate agricultural operations, enabling real-time data collection [15], analysis, and decision-making. Smart sensors like soil sensors [16], weather stations [17], livestock monitor [18], and pest detection sensors. The drones and aerial imaging [19] are used widely for crop surveillance, mapping, disease detection [20], and precision spaying [21]. IoT – connected drones stream live data to central dashboards. Smart greenhouse-controlled environments with IoT sensors [22] that monitor and regulate temperature, humidity, light intensity, and CO_2 levels [23] . The latest machinery connected each other like tractors, harvesters, and seeders embedded with GPS and IoT precision farming-planting, watering, and harvesting with high accuracy. Various applications of the smart agriculture is shown in Figure 1.

1.2 IoT based Technology for Agriculture

AI-powered analytics applied [24] to IoT data enables predictive maintenance, disease forecasting, and yield optimization [25]. The edge computing technology is jointly used for the data processing happens locally on devices, reducing latency, and ensuring real-time actions [26] in remote farm areas without stable internet. Blockchain and IoT [27] is used for supply chain traceability, ensuring transparency and authenticity of agricultural products from farm to consumer. The communication technology LoRaWAN and NB-IoT connectivity [28] is used for the low-power, long-range communication protocols are enabling affordable deployment sensors in rural regions. The vertical and urban farming is also important application of IoT in which automated, sensor-controlled environments are powering indoor farming, maximizing yield in small urban spaces. Smart farming [29] interest in warehouse monitoring is important. Digital equipment involves sensors and actuators for performing tasks spontaneously. IoT controls and co-ordinates agricultural routine work automatically. Spraying [29], weeding and watering [30] according to soil needs etc.

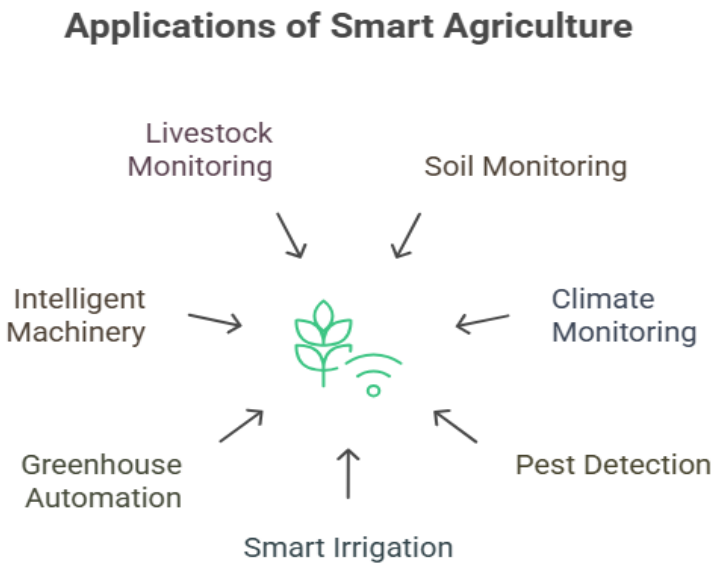


Figure 1. IoT smart technology trends in agriculture

2. LITERATURE REVIEW

AI algorithms [31] and data analyzation capability provides better approach towards the soil, weather, and crop data to determine the right time to sow, irrigate, and harvest [32]. With help of better and reduced resources wastage and increases the productivity. AI models can easily predict the agriculture practices [33] and activities like pest infestations, disease outbreaks, and weather patterns, enabling farmers to take preventative actions. This also can provide a better future yield forecasting and planning [34] with effective market approach. IoT provide a quick and accurate sensor combination which can easily monitor then real time values of weather and soil parameters [35]. This monitoring sensors can provide huge amount of data for the machine learning model to evaluate and analyze the data further. AI also helps to control irrigation systems to supply water/fertilizers [36] only when needed, saving water and increasing crop and soil health [37] . AI provides autonomous vehicles [38] like tractors, drones and harvesters that

can performs agricultural activities without intervention of human with precision and minimal cost reduction. Smart farming interest in warehouse monitoring [39] is important. Digital equipment involves sensors and actuators for performing tasks spontaneously. IoT controls and co-ordinates agricultural routine work automatically. Spraying, weeding and watering according to soil needs etc. smart farming [40] is new way of farming in which autonomous farming involves several new trends like vertical farming, autonomous farming control. The automation of water control in agriculture [41] is also very efficient and time saving concept due to status update of soil water activity activates. Agriculture ware house monitoring is also very effective area where IoT work more suitable. It is used to monitoring gaseous control, object detection and detecting threat used to control by smart sensor technology.

Combining IoT sensors and ML models [42] allows for site-specific management of crops, adjusting inputs like water and fertilizer to local conditions. From harvest to delivery, IoT tags and ML-powered logistics [43] help reduce waste and improve traceability challenges. It is not all smooth sailing. Many farms—especially smallholders—lack the infrastructure to support IoT devices or high-speed internet [44]. Data privacy, interoperability between devices, and the need for specialized technical knowledge are major hurdles. Moreover, ML models often require large, high-quality datasets, which aren't always available in agricultural settings.

2.1 Smart Irrigation

Proper Soil and water conservation [45] is crucial for agriculture. Soil moisture applied ecological parameters with soil may give an effective growth. The management of water for agriculture crops is challenging part of crop cultivation. The important application of IoT in research and development.[46] is to maintain and pour water with better quality and quantity as needed. Important factors for irrigation are environment, soil contents and water quality data. Control and monitor environmental parameters over the effect of sustainable irrigation management. Water requirement can be controlled involve some factors and can be maintained [47].

2.2 Livestock Monitoring

The livestock monitoring [48] involves technology, AI and IoT to track health, behavior, location, and productivity. The precision livestock farming the use of wearable sensors track animal health and movement, with ML models predicting disease outbreaks or identifying optimal feeding strategies [49]. The sustainable animal farming [49] provides health monitoring [50], productivity monitoring, behavioral analysis, environmental monitoring [51] , and Geo- tracking [52]. Many technologies evolve to provide a sustainable environment for the animal farming [51] like wearable collars or tags, leg or ear tags, in rumen boluses, smart feeders and waterers [53]. Whereas the computer vision [54] provides better vision for identification of lameness, body conditions and injuries. It also counts the animal detection and behaviors in pens, with monitors calving or unusual aggression.

2.3 Disease and Pest Detection

Diseases detection in machine learning [54] is major research area, especially in agriculture, forestry, and plant pathology. ML helps automate the identification of plant diseases and pest infections [55] from images, sensor data, or environmental conditions. Traditional machine learning approaches like feature extraction and classification used for the crop identification and classification [56]. The classifiers like SVM, KNN, Decision Tree and Naïve Bayes are widely used in traditional machine learning. Whereas as advanced field of machine learning termed as deep learnings which is used for classification and prediction from the image data [57]. The deep learning models like VGG16, ResNet, Mobile Net are most important models for leaf disease classification. Drones and stationary cameras feed images to ML systems that can spot early signs of stress or infestation.

2.4 Critical Analysis

The paper review covers a wide range of applications, from weather and soil monitoring to crop yield prediction. This will provide a new field area of landscape. It correctly pinpoints the synergy between IoT (Data collection) and AI/ML (data analysis and decision making) as the backbone of modern smart farming. A significant strength is the dedicated section on challenges including infrastructure, data privacy, data quality, technical knowledge is focused. This shows an awareness that the field is not just about technological triumphs but also about practical implementation barriers. The prediction model is used SVM with few good prediction features related to the dataset which is used in this study. This model performance is better to other basic ML models. Therefore, this model is used in this study.

3. RESEARCH METHODOLOGY

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An appropriate research methodology plays vital role in conducting the research in any domain like social science, applied science or engineering. Figure 2 illustrated the research methodology and the work plan to achieve the formulated objectives.

3.1 Data Collection

Data collection is important step in machine learning or AI based applications. In this regard the in this study data is collected by the IoT based module which integrated with different sensors, actuators, microcontrollers and power supply.

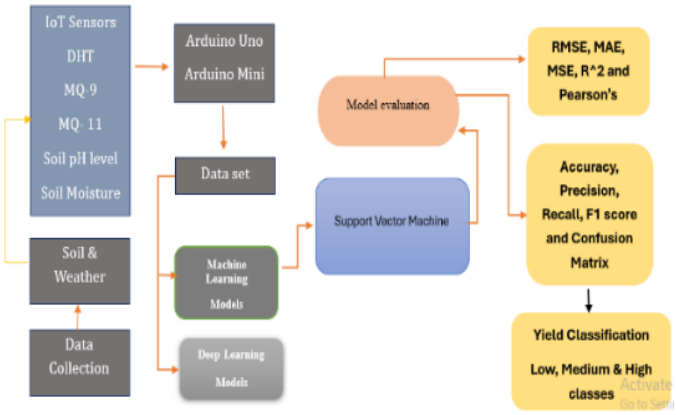


Figure 2. Methodology and work plan

3.1.1 Microcontroller

Arduino is a microcontroller board based on the ATmega328P. it's like the brain of an IoT s328P. it's like the brain of an IoT system-reading sensor data, processing it, and sending it to a display or network. Normally operating voltage of Arduino is 5V with the 7-12V reminded input voltage. The total analog input pins are 6 with 32KB flash memory for code. This board also consists SRAM with 2KB and EEPROM having 1KB size. The clock speed of Arduino is 16MHz with USB connectivity which is USB type-B for programming and power. The details of pin and sensors are tabulated in Table 1.

Table 1. Sensor Type and Pin type connection with Arduino

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

a. DHT

The temperature and humidity sensor are low-cost, digital sensor widely used in IoT, weather monitoring and agriculture projects. This sensor offers better accuracy and wider range. The DHT sensor has many features like temperature range is high from 〖-40〗 ^0C to 〖+80〗 ^0 C and humidity ranges from 0% to 100% RH. The DHT sensor is low power consumption and easy to interface with Arduino, raspberry Pi, ESP32 etc. this sensor is affordable

and scalable for large deployments. In agriculture DHT22 is used to monitor field microclimates, correlate weather data with crop health, low energy consumption. The diagram below shows pictorial view of the DHT22 sensor.

b. Soil Moisture

Soil moisture sensor is an essential component in smart agriculture. This is used in IoT based farming systems which helps to determine the water content in soil, which is crucial for irrigation management, crop health monitoring and resource conservation. The soil moisture sensor measures the volumetric water content in soil. The sensor uses capacitive or resistive methods to detect the presence of water. The common resistive sensor pin description is as VCC pin which is used for power supply ranging from 3.3V – 5V. the GND pin is used for ground, A0 analog output which is soil level. D0 is for the digital output the dry or wet status threshold set by potentiometer. The figure below depicts the soil moisture sensor clearly.

c. Soil pH Sensor:

Soil pH sensor is a device that measures the acidity or alkalinity of the soil. The pH scale runs from 0 (acidic) to 14 (alkaline), with 7 being neutral. Most crops thrive between pH 6.0 to 7.5, depending on the type. The sensor detects the hydrogen ion concentration in soil water content, converting it into voltage, which is then interpreted as a pH value. The figure below shows the soil pH level sensor with wire connectivity.

3.2 Data Preprocessing

3.2.1 Pandas

Pandas is a python library used for loading, cleaning, transforming, and exploring data before it is used to train models. It provides powerful data structures-especially data Frame and Series. It makes it easy to handle tabular data (like spreadsheets or database). With pandas, you can perform tasks such as handling missing values, filtering rows, merging datasets, computing statistics, and preparing features. Although pandas is not a machine learning library itself, it is an essential tool in the ML workflow because high-quality data preprocessing greatly improves model performance.

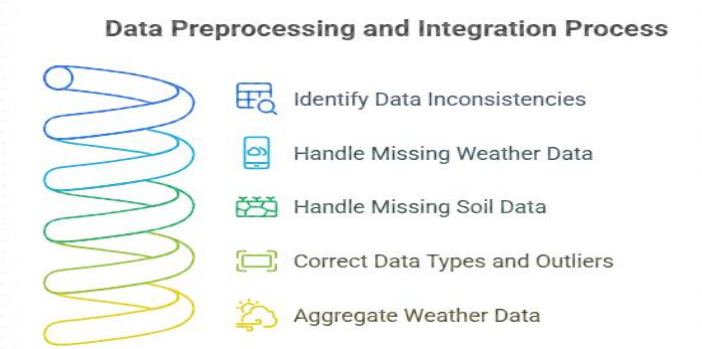


Figure 3. Data Preprocessing Techniques and Tools

3.2.2 Numpy

NumPy is a core python linearity used for fast numerical computing. It provides the ndarray, a powerful multi-dimensional array structure that allows efficient storage manipulation of large numerical datasets. NumPy includes tools for performing mathematical operations, linear algebra, random number generation, and vectorized computations-operations that are much faster than standard python loops. Many ML libraries (such as pandas, scikit-learn, TensorFlow, and pyTorch) are built on top of NumPy or depend on its array operations, making it a foundational tool for data preprocessing, feature engineering, and implementing ML algorithms.

3.2.3 *Matplotlib*

Matplotlib is a python library used for creating visualization that helps you understand and analyze data. It allows you to generate plots as line charts, bar graphs, histograms, scatter plots, and heatmaps. These visualizations are essential in ML for exploring data patterns, checking feature distributions, identifying outliers, monitoring training progress, and comparing model performance. Although, Matplotlib itself is not an ML tool, it is a key part of the ML workflow because clear visual insights lead to better model decisions. Data inconsistency occurs when the same data exists in different formats or values across various sources or within a single dataset. in this paper the dataset has few

inconsistencies like recording of soil pH level recorded as both "6.5" and "6.50" in different database fields, or the same weather station might provide temperature both Celsius and Fahrenheit. The data missing techniques are used as drop missing for data preprocessing step.

3.3 Model selection

The effectiveness in high-dimensional spaces SVM is very remarkable model to deal with. Weather and soil data create a high-dimensional feature space by considering features like daily temperature, humidity, solar radiation, soil pH, and NPK values, soil moisture at different depths. The SVM has also strong performance on non-linear relationships. In this study as we included agricultural input and yield are rarely linear relation. The SVM Model has also robustness to over fitting and strong generalization therefore, the primary goal in yield prediction is to build a model that performs well on new, unseen data from different seasons or field. The models that are too complex can overfit to the noise in the training data, failing to generalize.

3.4 Experimentation and results

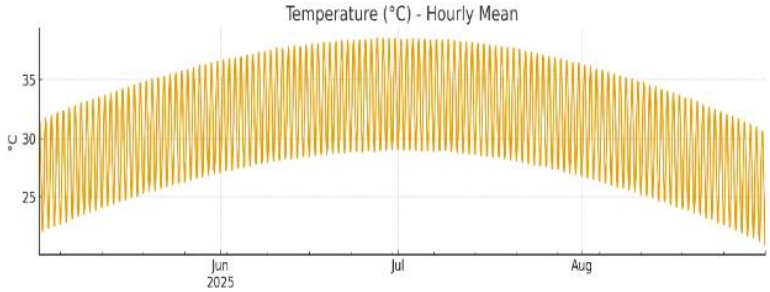


Figure 4. Temperature hourly mean

Seasonal and diurnal patterns drive temperature is depicted in Figure 4. Higher temperatures generally support cotton up to an optimal range; above that, heat stress can reduce yield class likelihood. Look for correlations between heat peaks and predicted 'medium','low' shifts.

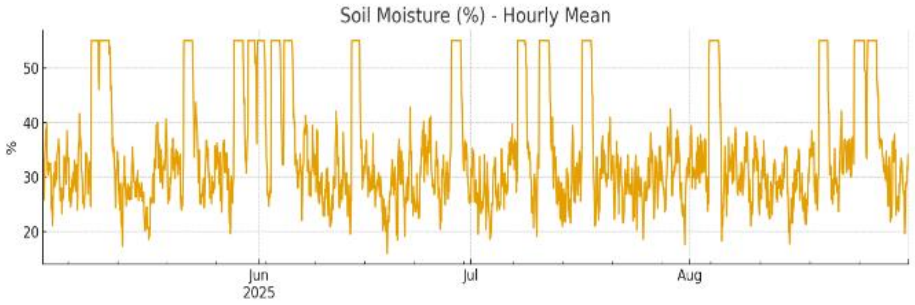


Figure 5. Soil moisture (%) - Hourly Mean

Figure 5 represents the soil moisture hourly mean, shows Soil moisture fluctuations reflect irrigation/rain events and evapotranspiration. Deviations below the optimal bands tends to decrease yield class; sustained moderate levels should align with more 'medium' and 'high' predictions.

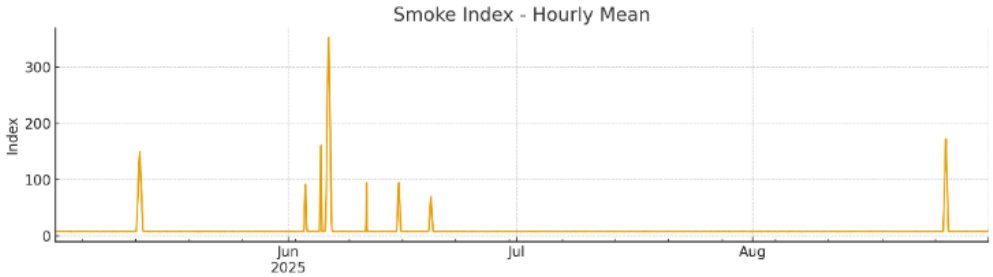


Figure 6. Smoke Index - Hourly Mean

The smoke spikes as illustrated in Figure 6, (e.g., wildfire periods) can depress photosynthesis and thus yield class. Check whether elevated smoke aligns with dips from 'high' to 'medium'/'low' in the time series chart.

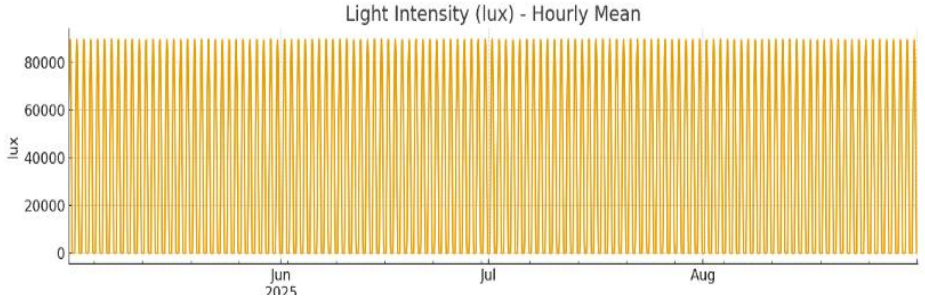


Figure 7. Light Intensity - Hourly Mean

Daylight follows a dome-like daily curve (Figure 7), higher midday light favors growth. Shorter days or overcast-like patterns (lower maxima) can reduce yield class likelihood.

3.4.1 SVM test metrics (Macro)

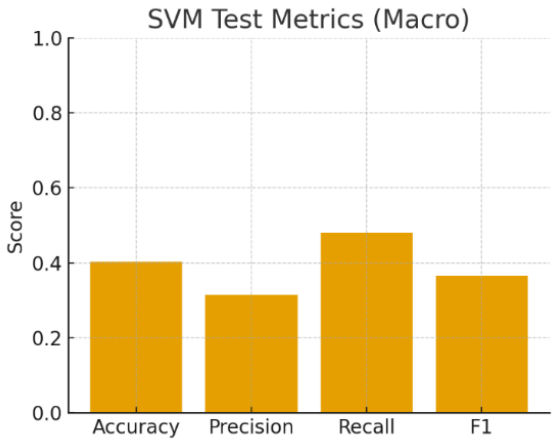


Figure 8. SVM Test Marics (Macro)

The overall performance on the held-out is illustrated in Figure 8. Accuracy reflects the share of correct predictions across the three yield classes (i-e low/medium/high). Macro precision is the average of the class-wise precision values. The macro recall averages the class-wise recall and give answers "of the actual instances of each class, how many did the model capture?

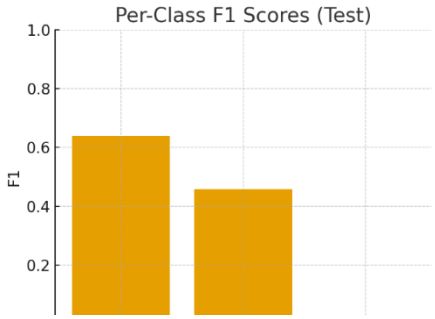


Figure 9. F1 Score per class (Test)

According to the Figure 9, the F1 score is the harmonic mean of precision and recall per class, then averaged; it balances false positives and false negative and is robust when classes are imbalanced.

3.4.2 Confusion Matrix (Low/Medium/high)

SVM classification true vs predicted classes is obtained below in figure 10. the predicted classes are low/medium/high**.** Diagonal cells are correct predictions, off-diagonal cells show confusions. If 'medium' is frequently confused with 'low' or 'high', it suggests boundaries between classes are gradual or features overlap in those regimes. Systemic confusion (e.g., many 'high' , 'medium') may indicate thresholds or features (like soil moisture or temperature) that need sharper modeling or additional predictors.

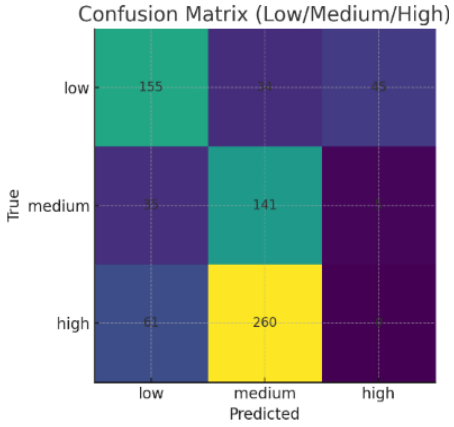


Figure 10. SVM confusion matrix true vs predicted class

Permutation importance features measure the drop in the chosen score after randomly shuffling one feature at a time is shown in Figure 10. Higher bars indicate features the model relies on more for good F1 performance. If Moisture or temperature rank highly, it confirms agronomic intuition that water and thermal regimes drive yield class.

3.4.3 Permutation feature importance F1-macro and Balance accuracy (Test set)

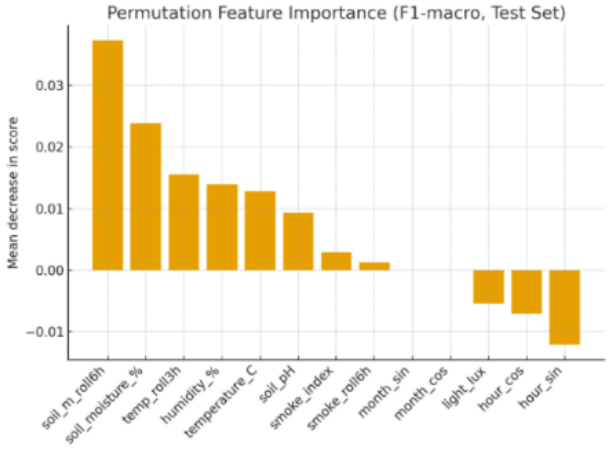


Figure 11. Permutation feature importance F1-macro and balance accuracy

In Figure 11, this variant uses balance accuracy, which averages per-class accuracy. It helps when classes are imbalanced by giving equal weight to each class. Compared with the F1-based ranking, it is stable top features across metrics indicate robust drivers; differences may reveal where precision vs. recall trade-offs matter.

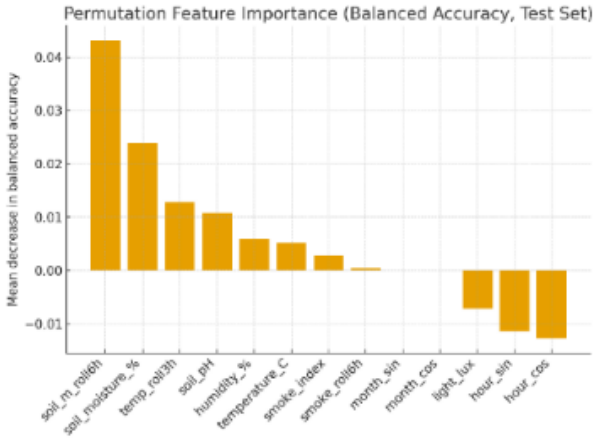


Figure 12. Permutation Feature importance (Balanced Accuracy, Test Set)

3.4.4. Rolling Precision/recall for low and medium class

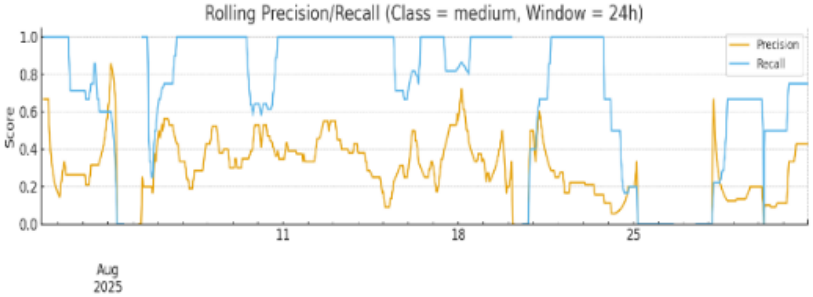


Figure 13. Rolling precision recall class = medium window = 24hr

It is quite evident from Figure 13 that 'low' often spans transitional conditions, fluctuations are common. Sustained recall drops suggest the model is diverting predictions to 'medium' or 'high' during certain regimes; precision drops suggest many false 'low' flags.

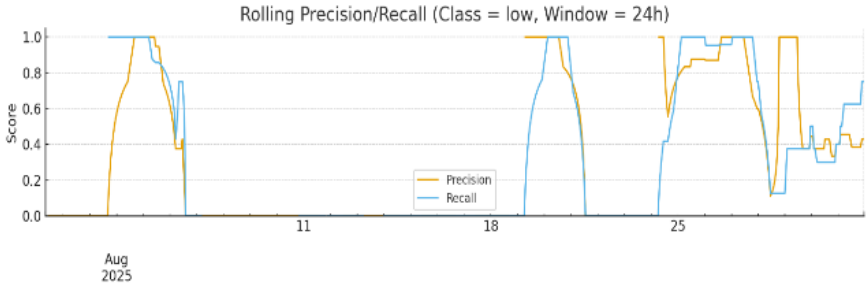


Figure 14. Rolling precision/Recall for class low, window 24h

In Figure 14 because 'medium' often spans transitional conditions, fluctuations are common. Sustained recall drops suggest the model is diverting predictions to 'low' or 'high' during certain regimes; precision drops suggest many false 'medium' flags.

3.4.5 Hourly test set and Prediction of each parameter

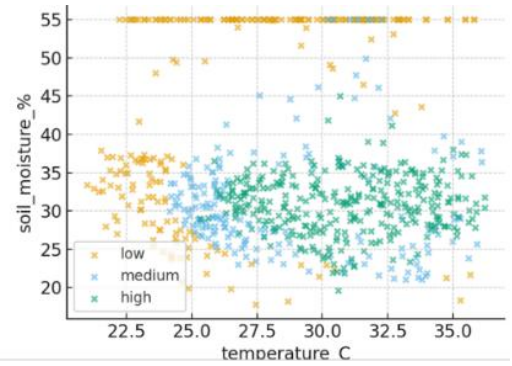


Figure 15. Hourly test set and prediction of each parameter

In Figure (15), each point is an hour in the test set, colored by true yield class. Clusters reveal how classes separate in the feature space. If 'high' concentrates around moderate-to-high soil moisture and warm temperatures that supports the model's reliance on these signals.

3.4.6 Prediction of Yield class (Low, Medium and High)

In Figure 16, the yield class may drop when smoke is high even if soil moisture is adequate. Indicating photo inhibition effects. Look for 'high' class points thinning out as smoke increases. Whereas the Figure 17, this classic psychrometric slice shows whether very hot/dry or cool/damp corners correlate with lower yield classes. An arch-like cluster for 'medium' can indicate transitional comfort bands for cotton.

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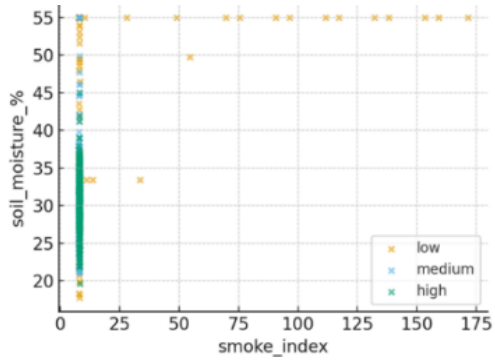


Figure 16. Soil Moisture vs Smoke index

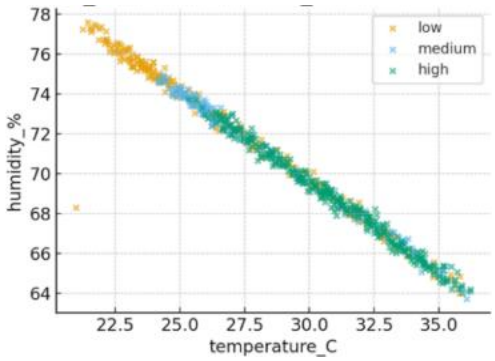


Figure 17. Humidity vs temperature

The interaction of atmospheric conditions is illustrated in Figure 18. High light with moderate humidity often favors growth; excessively low humidity at high light may induce stress and reduce yield class.

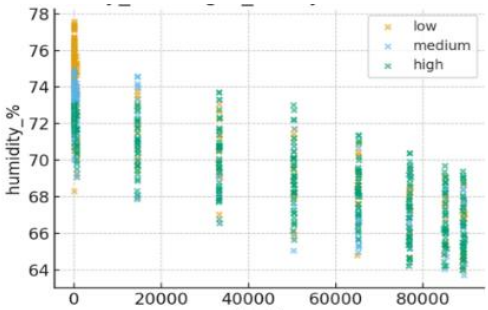


Figure 18. Humidity Vs Light intensity

3.4.7 Hourly Yield class: True Vs predicted

Figure 19 shows a time series comparing the ground truth yield class with the model's predictions over the test period (0=low, 1=medium, 2=high). Alignment between the lines indicate correct predictions. Persistent offsets (e.g Model under-predicts to 'medium') show bias. Periods of high volatility can coincide with transitional weather (e.g heat spikes or abrupt moisture changes), making classification harder.

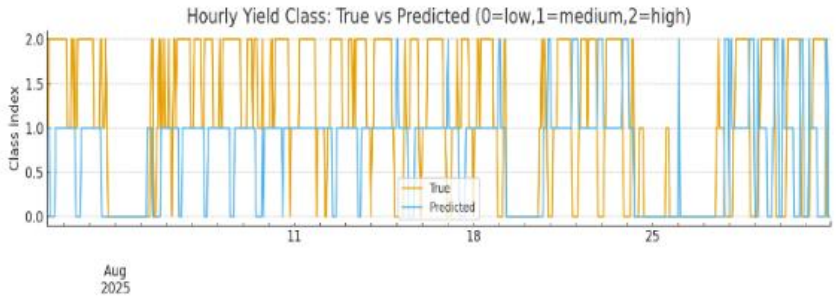


Figure 19. Hourly yield class: True Vs Prediction (0=low, 1=medium, 2=high)

3.4.8 Training vs validation accuracy

The Figure 20 shows Model training and validation accuracy, the blue bar shows 0.98 accuracy whereas the orange bar shows validation accuracy having 0.87%.

The model's accuracy and loss on both training and validation sets over the epochs were generated to assess training progress and identify potential overfitting is illustrated in Figure 21. The Y-axis shows the accuracy, which measures the proportion of correct predictions made by model on training and validation sets. It ranges from 0 to 1. The blue line tracks the accuracy on the training set after each epoch. Initially, training accuracy starts low but increases rapidly as the model begins learn from the training data. As the model trains for more epochs, the training accuracy steadily improves, showing that the model is learning to make predictions based on the training data. The validation accuracy is measured in the graph by orange line. The accuracy on the validation set, is measured for the model's generalization ability as how well it performs on new, unseen data. The validation accuracy starts lower than the training accuracy because of the model is initially not optimized to generalize well to unseen data.



Figure 20. SVM Model training accuracy and validation accuracy

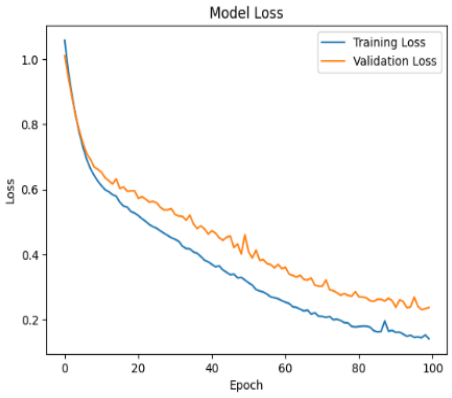


Figure 21. Model training loss vs validation loss

4. CONCLUSION

This study provides a Machine learning and IoT based approach for the yield prediction. This provides a better approach for the classification of yield in three classes as low, medium and high form the training of collected data. The integration of IoT (Internet of things) with smart agriculture enables real-time monitoring, automation, and data driven decision-making more efficient, sustainable, and less labor-intensive. The IoT sensors collect soil conditions, weather parameters like temperature, humidity, rainfall, and crop health. The results summarize overall performance on the held-out. Accuracy reflects the share of correct predictions across the three yield classes (i-e low/medium/high).

Permutation importance features measure the drop in the chosen score after randomly shuffling one feature at a time. The time series compares the ground truth yield class with the model's predictions over the test period (0=low, 1=medium, 2=high). Periods of high volatility can coincide with transitional weather (e.g heat spikes or abrupt moisture changes), making classification harder.

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