ISSN:1813-1786 (Print) 2313-7770 (Online)

A Deep Learning Hybrid Framework CNN-LSTM Agricultural Classification of Yield

A. A. Mirani[1], N. Memon[2], S. Iqbal[3], I. K. Jatoi[4], I. A. Memon[5]

[1]Department of IT, Shaheed Benazir Bhutto University, Shaheed Benazirabad, Sindh, Pakistan
[2] Computer Science, Government Girls' Degree Collage, Nawab Shah, Sindh, Pakistan
[3] Bahauddin Zakariya University, Multan, Punjab, Pakistan
[4]Department of Statistics, Shaheed Benazir Bhutto University, Shaheed Benazirabad, Sindh, Pakistan
[5]Department of IT, Sanghar Campus, Benazir Bhutto University, Shaheed Banzirabad, Sindh, Pakistan

[3] shahid.iqbal@bzu.edu.pk

Abstract- The research proposed the hybrid framework of the deep learning which combines CNN and LSTM for the yield prediction by the IoT based sensor data of weather and soil. The spatial features are extracted by CNN model from the non-linear dataset having different heterogenous datasets parameters as humidity, light intensity, soil pH level, smoke level and with additional layers of LSTM are used to capture temporal dependencies in the obtained time – series analysis of the data. The data is collected by the integration of the IoT based sensor module and data preprocessing is performed as labeling, reshaping, label encoding, and normalization of the data. The hybrid model further enhanced with the integration of the L2 regularization, which is trained over 100 epochs with additional adam optimizers. The Hybrid model is with L2 regularization results high score of accuracy as 93.24 with 1.1822 loss which shows robust performance among all compared models. This framework study provides efficient integration of Deep Learning and IoT abased integration in agricultural data driven decision for yield prediction.

Keywords- CNN-LSTM, Precision Agriculture, Crop Yield Classification, Deep Learning, IoT, Smart Agriculture Farming, Data Evaluation.

I. INTRODUCTION

Agriculture sector in nawab shah, Sindh, Pakistan is very crucial. The sustainability of the crop productivity is basis on the different environmental and soil conditions [1]. This sustainability can be affected by the different factor which also influences on the yield estimation. This region needs to transfer from the traditional methods to data-driven decision on the basis of agricultural data, this can help for the optimized decision making with sustainable farming [2]. The 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 real-time environment with effective methods of data driven approach. The critical factors like temperature, humidity, light intensity and other important factors can be monitored by deploying IoT based infrastructure.

Today's industry sees Machine Learning (ML) evolving from narrowly focused, task-specific solutions to generalized, flexible, and highly efficient solutions. [3] 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 [4]. Self-supervised and few-shot methods are being developed to reduce dependency on large-scale labeled datasets, thus providing greater accessibility to ML technologies in domains with minimal annotated data [5]. Simultaneously, multimodal learning is being developed, which allows models to procedure and different types of data (text, images, audio, sensor) within a single framework. making them applicable to problems highlighted classification, regression, detection of images with data pattern recognition [6]. However, training DL models involves a huge data as well as computational resources, which can be achieved through the use of GPUs or other dedicated hardware. ANN and deep learning have carried about a areas such as computer vision, speech recognition, self-driving cars, and recommendation systems.[7], Data-driven technologies and analytics in agriculture and environmental monitoring can be used to improve crop production, optimize resource use and create sustainability. Technologies like sensors, unmanned aerial vehicles (drones), and satellite remote sensing provide comprehensive data in the field of agriculture in terms of soil properties, weather patterns, plant development, and water usage. [8-9].

The paper proposed the novel hybrid CNN-LSTM framework. the hybrid model is designed to harness the two architectures CNN mechanism for extorting the important features from the data given as input such as soil and weather, whereas LSTM is used for how spatial features learned as long-term dependencies as per time. This is as influenced by the weather data patterns and which can help to manage practices. The implementation of real-time dataset using CNN-LSTM model, which focuses on time-series of IoT sensors data readings. The important steps or objectives are (1) to design a hybrid CNN-LSTM model for the weather and soil data reading captured by IoT modules; (2) the Model is further altered with L2 regularization and compared with traditional model; and (3) the real-time farmwork integration of IoT based data values with the deep learning, which provides the more sophisticated, intelligent and sustainable yield prediction.

II. Problem Statement

The multi-model data collection with integration of the IoT based module is important aspect of the industrial and agricultural applications. However, this is more challenging to make data feasible for the extensively training and testing AI models. The deep learning architectures integration with IoT based data collection for agricultural applications provides more challenging part of the research opportunity. The traditional deep learning models can provide detailed insight of the data but having few complexities like data, time, and training accuracy. To address this problem, the novel hybrid model CNN-LSTM is proposed to fuse the important features of the weather and soil for the yield prediction.

Objective:

- To design a hybrid CNN-LSTM model for reading captured by IoT sensor data
- The Model is further altered with L2 regularization and compared with traditional model.
- The real-time farmwork integration of IoT based data values with the deep learning, which provides the more sophisticated, intelligent and sustainable yield prediction.

Novelty of Study:

Hybrid architecture CNN-LSTM for agriculture:

- The proposed study provides a novel approach with CNN for the spatial feature extraction and LSTM is used for the temporal dependencies in obtained patterns of the dataset.
- The field data is captured with real-time sensor module, further this obtained data is fed to the hybrid model.
- Regional Cotton Case study:
  This study provides the basic and specific regional cotton crop data, which exhibits extreme temperatures.
- L2 regularization for improved generalization:
  For the reduction of the overfitting the L2 regularization is used on the sensor-based data.
- Pipeline for the precision agriculture:
  The deployment of the sensor, data acquisition, with effective preprocessing for the yield prediction providing the hybrid deep learning approach better practical approach for the stockholders.

III. Literature Review

Environmental surveillance applies systematic data collection and analysis to produce information about the quality of the atmosphere and water, climatic pattern, biodiversity index, and the load of pollutants. This technology is the basis of early warning of the natural hazards, pollution control methods, and sustainable management of the ecosystem. The intersection of agriculture and environmental surveillance using data-driven technologies encourages sustainable resource use, adaptation to climate change, food security and environmental protection.[10]. Sensors, remote sensing vehicles, and IoT is used to provide real-time datasets that are analyzed using analytical frameworks and predictive models to identify the developing trends, threats, and regulatory gaps. [11] and deep learning. Intersection between the IoT and ML has given rise the growth of various areas. 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 optimization [12]. This has catalyzed the adoption of PA, the strategy that practices latest technological trends to ensure the progress soil with irrigation system [13]. CPS is integration of smart and intelligent physical systems having computational control and management, where sensors and actuators are integrated to monitor and bring under control the physical processes. The combination of the Internet of Things (IoT) and Cyber-Physical Systems (CPS) is a good example of how machine learning (ML) and artificial intelligence (AI) can be used to improve the functionality and autonomy of networked physical systems. [14] CPS with ML capabilities in smart manufacturing can optimize the production lines, predict machine failures, and increase efficiency via real-time corrections [15] the plant disease detection model [16] used for the image detection which provides disease classification and detection with good accuracy. Whereas another [17] study provides a framework for the crop monitoring using IoT based architecture with integration of the machine learning. The IoT with the integration of DL models, challenges and latest trends are discussed in [18]. The study investigated the yield predication and image data based diseases prediction using RNN and CNN models [19]. The study in [20] provides the integrated approach of the data integration and augmentation for the yield prediction. The study [21-22] provides the detailed overview the IoT and deep learning techniques in PA for environmental measures values of parameter, yield prediction and management techniques of soil. This technological advancement can insight depth analysis of the soil multi-parameter environment includes soil moisture, temperature, pH levels, NPK (Nitrogen, Phosphorus, potassium) content, and electrical conductivity [23]. The wireless sensor networks [24] are used for the arrays of sensors deployment across the fields using protocols like LoRaWAN, ZigBee, and low-power communication. Depth profiling sensors are used to monitor soil conditions at various depths to understand root zone dynamics and water movement [25]. The environmental monitoring is useful for the plant conditions and growth. Weather stations are integrated systems which is used for measuring temperature, humidity, wind speed, solar radiation, and precipitation [26]. Furthermore, microclimate sensors are integrated and deployed at crop canopy level to capture field-specific climate variations. The plant surface moisture can be identified by using leaf wetness sensor for assessment of disease risk [27]. The crop health monitoring is monitored by using spectroscopic sensors, thermal imaging [28] and hyperspectral sensors are used to capture chlorophyll content, nutrient status, water stress, spectral signatures for precises health assessment respectively[29]. The IoT based network architecture very remarkable using technology as edge computing[30], cloud integration [31] and hybrid systems provides a time-sensitive data reducing latency and bandwidth requirements, centralized data storage, heave computational task etc. Whereas, deep learning provides hybrid approach [32] for the combine spatial feature extraction from satellite/drone imagery with temporal analysis of weather and sensor data [33]. Transfer learning approach adapts pre-trained models on limited agricultural datasets for specific crop varieties and regional conditions [34]. Furthermore, attention mechanisms are adopted to focused on critical growth stages and environmental factors affecting yield. The predictive analytics algorithms [35] are widely adopting in deep learning for agriculture yield [36] trajectories based on data on historically conditions. The DL models for risk assessment for the identification factors likely to impact yield quality and quantity. The anomaly detection techniques like autoencoder are used to learn normal growth patterns and flag deviations indicating potential issues. GANs [37] create artificial data for stress scenarios.

IV. Methods and Design of Study

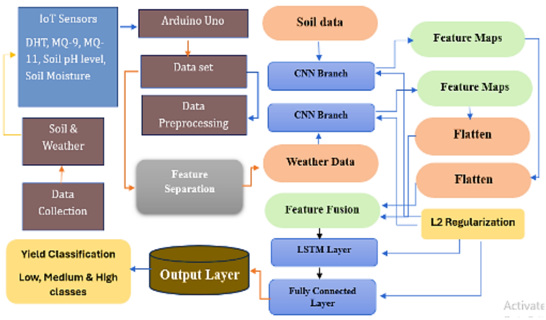


Figure 1 Methodology and Model Architecture Design

Data Collection Parameter:
Data set is used to prepare weather and soil parameters. The parameters for weather include temperature, humidity, smoke, light intensity, soil pH level, soil moisture, area, crop type and total yield. The temperature unit for dataset is $℃/℉/K$. The temperature is important part of plant growth and impacts on crop yield with several stages from seedling to final yield.

1. *Temperature and Humidity:*

The temperature in Nawab Shah, Sindh, Pakistan always remains high during the season of cotton crop. The temperature rises from 30^0 C to 49°C. the recording shows very intensive high temperature which is almost not found in previous datasets which are available on Kaggle or other data repositories.

Types:
- Maximum Temperature – highest daily value
- Minimum Temperature – Lowest daily Value
- Average Temperature – daily mean value
- Soil Temperature – at surface or below (important for seed germination)

Relative humidity (RH) can is calculated as
Formula:

$$Relative\ Humidity\ (RH) = \left(\frac{Actual\ Vapor\ Pressure}{Saturation\ vapor\ pressure}\right) \times 100\%$$

Alternatively, its often measured using temperature and dew point:
$RH \approx 100 - 5 \times (T - T_{dew})$
Where:
- T = Air temperature (℃)
- T_{dew} = Dew point temperature (℃)

2. *Light Intensity:*

The light intensity is one of the most critical factors influencing cotton physiology, photosynthesis, growth stages, and ultimately yield and fiber quality. Light provides energy for photosynthesis, the process by which cotton plants produces carbohydrates needed for vegetation growth (leaf and stem development), flowering and boll formation, boll maturation and fiber elongation. Light intensity affects the cotton crop at various stages. The table below is given a detail of growth stage and light intensity impact.

Growth Stage	Light Intensity Impact
Seedling Emergence	Low light delays emergence, weakens early growth
Vegetative Growth	High light promotes strong stems, large leaves, and more branching
Flowering	Adequate light ensures robust flower development and pollination
Boll Setting	High light encourages more boll retention and higher carbohydrate supply to developing bolls.
Fiber Elongation	Optimal light improves fiber length and cellulose synthesis

Effects of Low Light /Cloudy Conditions:
Reduces photosynthesis, limiting energy for boll development with increase boll shedding. Whereas, this leads to smaller bolls, shorter fibers, and lower yield. The low light effect may also cause excess vegetative growth (more leaves than reproductive parts).

3. Smoke:
The impact of smoke on cotton crop may occur in physiological and agricultural effects. Smoke, whether from wildfire, stubble burning, or industrial pollution, introduces aerosols particulates and gaseous pollutants. The smoke may affect in terms to reduce photosynthesis process such as smoke particles block or scatter sunlight, reducing photosynthetically active radiation (PAR), chlorophyll absorption is lowered. Another issue which causes by stomatal blockage like co2 intake which impacts slower photosynthesis process and poor cooling and water regulation, leaf damage and chlorosis.
The photosynthesis reduction due to smoke can mathematically represented as,

$$A = A_{max} \cdot \frac{I}{I+K}$$

Where: A = Actual Photosynthesis rate ($\mu mol\ CO_2\ m^{-2}\ S^{-1}$), A_{max} maximum photosynthesis rate, I is incident PAR after smoke attenuation and K = light saturation constant

4. Soil Moisture:
The critical factor in agriculture is soil moisture status for the healthy development of cotton crops, as it directly makes influence on the water and photosynthesis process. Cotton is sensitive at key stages like flowering and boll formation. Cotton requires adequate and balanced soil moisture throughout its growth period. Both deficit and excess soil moisture can negatively impact on root development, crop metabolism, and ultimately yield and fiber equality. The soil moisture can affect on different stages of cotton crop from different aspects give as

Table 1 Moisture Deficit Stages and its Effects

S. No.	Stages	Moisture Deficit Effects
1	Germination	Poor seedling emergence, uneven stands
2	Vegetative Growth	Stunted growth, fewer leaves, shallow roots
3	Flowering	Flower shedding poor pollination
4	Boll Formation	Reduced boll count, smaller bolls
5	Boll Maturation	Poor fiber elongation, reduced weight, lower lint yield

The optimal soil moisture range falls below categories as:

Table 2 Soil Moisture Optimal Range for Cotton Crop

S.No.	Parameters	Optimal Range for Cotton
1	Soil Moisture	60%-80% of field capacity
2	Soil Water Potential	-30 to -60 kPa
3	Volumetric Moisture (%)	15%-25% (depends on soil type)

Cotton prefers well-drained loamy soils, waterlogging or dry cracking clay soils can both be harmful. The root rot, poor nutrient uptake can cause by root oxygen deficiency and increased fungal infections like fusarium, phytophthora, which also causes delay in maturity and poor boll opening with higher shedding of reproductive organs.

5. Soil pH Level:
Soil pH is key chemical property that directly affects nutrient availability, root health, and microbial activity in the soil. For cotton, correct pH range is vital to cotton crop optimal growth, boll development, and high fiber yield. Soil is pH is measured of acidity or alkalinity of the soil, defined as $pH = -Log_{10}\,[H^{+}]$. *Further* Scale: 0 (very acidic) to 14 (very alkaline) and Neutral: pH 7.0. the optimal Soil pH for cotton crop.

Table 3 Soil pH Range for Cotton Crop Suitability

S.No.	Soil pH Range	Sustainability for Cotton
1	5.5 – 6.5	Ideal range for cotton crop
2	6.5 – 7.5	Good/Neutral
3	<5.5	Too acidic – nutrient toxicity risk
4	>7.5	Too Alkaline – nutrient look up

How Soil pH Affects Cotton Crop?
pH controls the solubility of nutrients in the soil such as Low pH <5.5: deficiency of Ca, Mg, Mo; toxicity of Al, Mn and High pH >7.5: deficiency of Fe, Zn, Cu, P. Whereas extreme pH levels cause poor root elongation, root tip burn (acidic), decreased water and nutrient absorption. The microbial activity of pH also affects the soil microbial life, especially nitrogen-fixing bacterial and mycorrhizae, which support cottons growth.

Effects of Improper pH on Cotton:

Table 4 Effects of Improper Soil pH Level

S. No	Problem Caused	If pH is too Low (Acidic)	If pH is too High (alkaline)
1	Nutrient Deficiency	P, Ca, Mg	Fe, Zn, Mn, Cu
2	Root Damage	Al and Mn toxicity	Na toxicity (in sodic soils)
3	Boll Development	Reduced due to poor N & P uptake	Reduced due to Fe and Zn lockout
4	Disease Susceptibility	Root rot & fungal issues	Wilt diseases in dry calcareous soils

Crop Area and Type:
The three Acre cotton crop is selected for the study to monitor above mentioned parameters. The cotton crop is used to study the weather and soil parameters in this study. Village Haji Fida Hussain Mirani, Near Bakhtawar Cadet Collage Road, District Shaheed Banzirabad, Sindh, Pakistan.

Experimentation and Tools:
The following table shows details of experimental software tools used in this study:

Table 5 Experimental Study Software Tools Used

Tool	Version	Purpose
Google Colab	Pro	For coding and simulation of dataset
Python	3.13.9	For coding instruction, Model training, & programing
ML Libraries	TensorFlow, Numpy, pandas, matplotlib, stat, and other	For mathematical, number values, and visualization
Excel	MS Excel 2016	For dataset preparation

Data Collection Hardware Tools:
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. An IoT module in agriculture typically needs to develop when data is collected from the dense areas, where human is not reachable or difficult to measure the data. In this study data is collected by deployed sensor module.

Why Arduino Uno for Agriculture Applications?
The Arduino is used for several factors and features like simple to use, supports many sensors, reliable in field conditions, wide community support, low cost, and portable.
The Pins and sensors connection detail is as below table:

Table 6 Sensor Type and Arduino Pin Type

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

Hybrid Model Implementation:
1. Data loading, initial inspection & Data preprocessing:

The dataset is uploaded on google derive to link drive with Google Colab. The data location is https://colab.research.google.com/drive//content/svm_predictions_3class.csv. The data is loaded into pandas Dataframe. The initial rows of the

DataFrame were displayed to verify dataset. The preprocesss_data function was defined and applied to the loaded DataFrame. This function performs the crucial steps like dropping irrelevant columns, separating features and labels, feature scaling, label encoding, Train-Test split, reshaping CNN-LSTM.

Hybrid CNN-LSTM Model Definition:
Separate functions, build_cnn_model and build_lstm_model, were defined to create individual CNN and LSTM model architectures. The sequential named CNN has included many processes from convolutional layers to dense layer. The adam optimizer is used for the feature compilation additionally. The sequential LSTM model with an LSTM layer, regularization dropout, and a dense output layer. This further compiled using optimizer named adam. A combined model was constructed by defining an input layer and then creating separate CNN and LSTM branches that operate on this input. The output of these branches was concatenated, followed by dense layers for further processing, and finally SoftMax activation is used for the multi-classification in dense layer.

Hybrid Model Evaluation and Testing:
The combined trained model using preprocessed data using 100 epochs. Further 20% of spilt validation is obtained by using the same data. In last training loss and accuracy is calculated fort the validation set and training set. Figure 2 shows the correct classified and misclassified medium

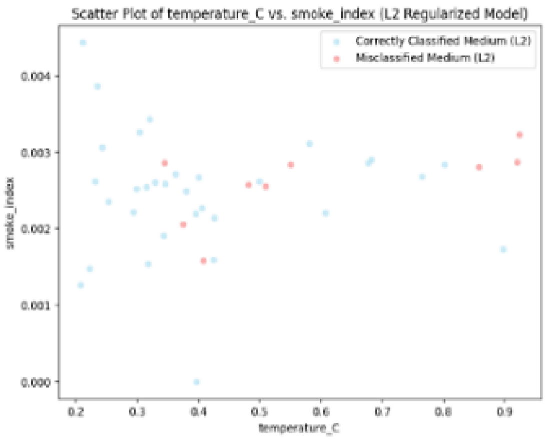


Figure 2 Temperature vs smoke

L2 Regularization Classified and Misclassified Medium:
The graphs (3) show temperature vs. humidity classification which is shows distinct inflecting the environmental patterns. The correctly classified clusters are temperature-humidity value ranges while medium L3 is more scattered by the spectrum of the environment. The misclassified points with medium L3 across the whole spectrum of environment.

The output of graph suggest CNN-LSTM gives reliable output with suitable conditions with same environment specially in moderate temperature ranges around 0.5 to 0.7 and 0.3-0.6 humidity levels.

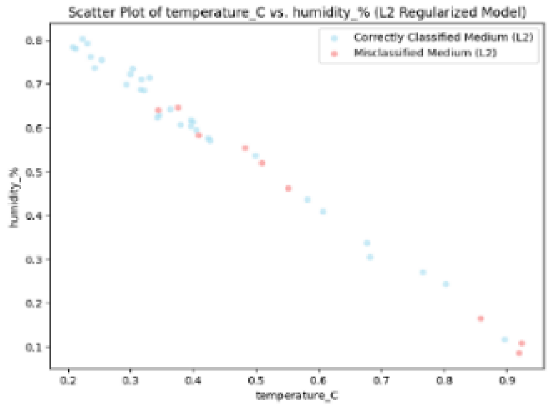
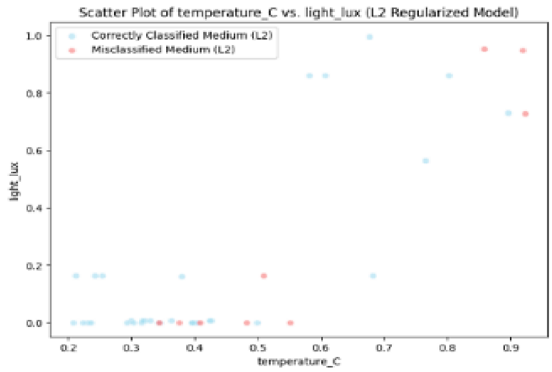
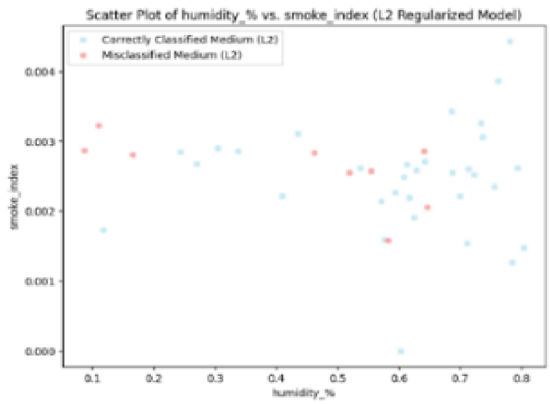


Figure 3 Temperature vs Humidity

The above graph 3 (b) shows the labeled “medium labeled” are just for the distributed temperature (x-axis) and the smoke is (y-axis).



(a)

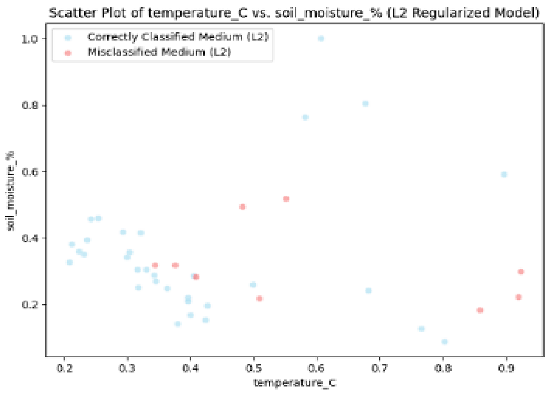


(b)

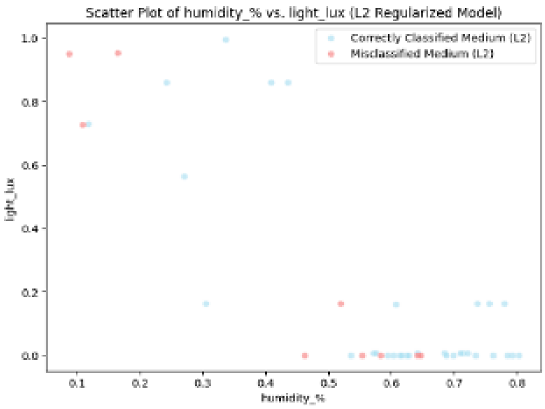
Figure 4 (a) Temperature Vs Light (b) Humidity vs Smoke

The plot 4 shows two graph (a) temperature vs light and (b) humidity vs smoke.
In figure 5(a) the light levels across the temperature with outlier of light handful. The blue dots are

dominated and red appears low_lux cluster need high temperature which suggest the light and temperature don't separate the class. Due to that reason model predict correctly. In figure 4 (b) the figure shows prolix with smoke in narrow band and whereas the humidity is spinning around the range widely. Further it also shows no boundary, the similarly and smoke levels are misclassified.



(a)

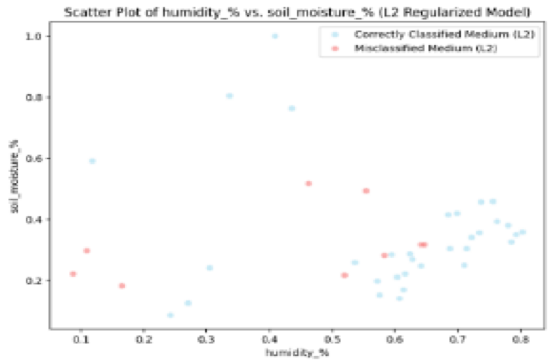


(b)

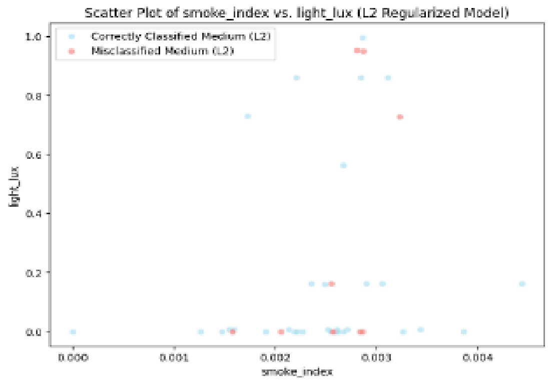
Figure 5 (a) Soil & Temperature (b) Humidity & Light using L2 Regularization

The plot 5 (a) shows negative pattern and high trends of temperature with lower soil moisture. while more moisture variability has been seen with cooler temperatures. The largely correct cross the space features by the model with L2 regularization with low soil moisture as mid to high temperature, which give clear hint that moisture level borderline conditions are typical for the model. Figure 5 (b) plot shows inverse relationship, where light is high due to low humidity and higher humidity causes zero light. The correct classified points and misclassified scattered.

In figure 6 (a) the points scattered upward show Higer humidity which generally accords with higher value of soil moisture. this shows the formation of loose positive correlation and blue dots are for mid-high humidity ($\approx 0.55 - 0.8$), also with soil-moisture band reasonably, while lower humidity shows error sprinkled around the zero transition, which suggests the ambiguity of the boundary, where air is dry or mid-range soil moisture. further in figure 6 (b) the low light distribution is obtained cross the narrow smoke range ($\sim 0 - 0.004$), with high light outliers near the mid-levels of smoke.



(a)



(b)

Figure 6 (a) Soil vs Humidity (b) Light vs Smoke

The blue is for the correctly classified and red points are for the misclassified point which shows heavily overlapped.

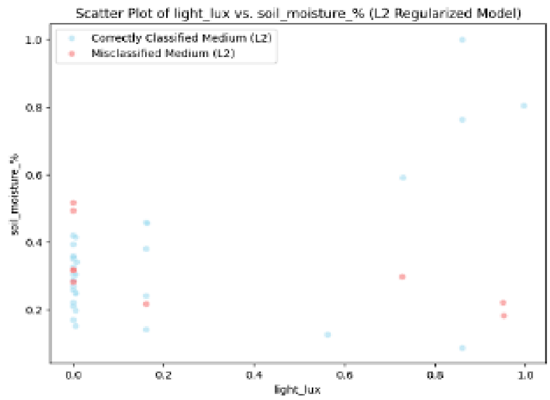


Figure 7 Soil Moisture vs Light Intensity

The plot in figure 7 shows cluster near 0 across the soil moisture, with few outliers of bright-light at low and very high soil moisture. the low-light cluster outliers are misclassified which indicates light alone near zero does not differentiate.

Model Training and Validation:

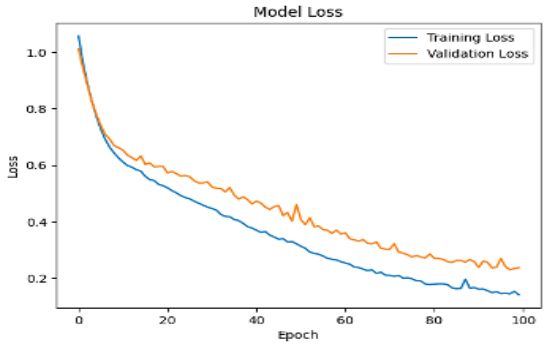


Figure 8 CNN-LSTM Hybrid Accuracy

Plot in figure 8 shows accuracy and loss of model for training and validation epochs were generated to assess training progress and identify potential overfitting. The Y-axis is measuring the accuracy 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 dataset. the model training for more epochs, the training accuracy steadily improves, learning to make observation for prediction on training dataset. The validation accuracy is measured in the graph by orange line. The accuracy is measured on validation dataset for generalization of model ability as how well it performs for the experiment on new data. The validation accuracy is lower whereas training accuracy is high because model initially is not optimized to generalize well to new data. Over a certain time validation accuracy improves as the model learns better patterns, however after certain point (around 30-40 epochs), the validation accuracy seems to plateau or fluctuate more as compared to training accuracy, shows model might be overfitting. In this graph training accuracy is increasing smoothly, but the validation accuracy stagnates or fluctuates after reaching a peak. The between training and validation accuracy gaps indicates model might be overfitting. As more complex model, it gives memorizing training data instead of generalizing, which leads to lower performance on validation data.

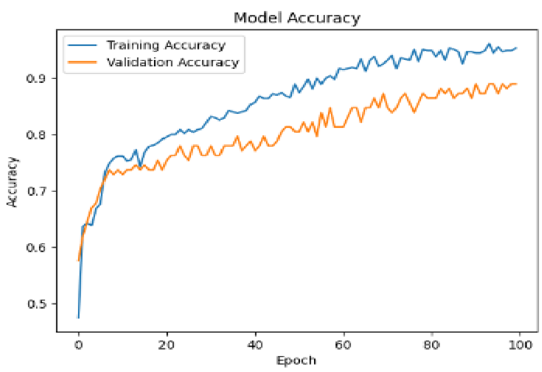


Figure 9 CNN+LSTM Hybrid Model Training vs Validation Loss

Figure 9 Shows training and validation loss decrease smoothly throughout training, with validation consistently above training and showing mild noise. The sustained downward trend without divergence indicates stable learning; the persistent gap mirrors the small overfit seen in the accuracy plot.

Confusion Matrix:

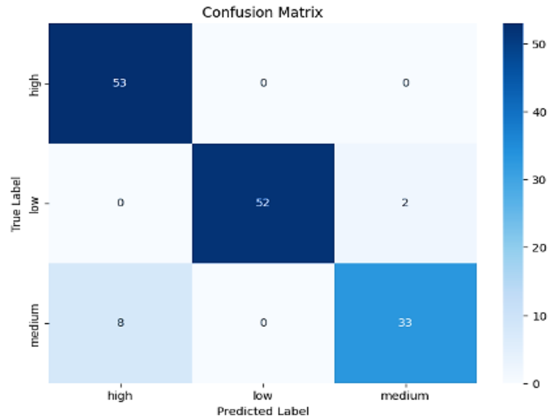


Figure 10 Hybrid CNN+LSTM Model Confusion Matrix

The confusion matrix is generated for the prediction of true perdition values with false perdition.
In Figure 10 performed simulation on each class as, class ‘high’, the model correctly classified 53 instances as ‘high’ and did not misclassify any ‘high’ instances as ‘low’ or ‘medium’. for class ‘low’, model correctly classified 52 instances as ‘low’. It misclassified 2 instances as ‘medium’ and o as ‘high’. In last class ‘medium’, the model correctly classified 33 instances as ‘medium’. It misclassified 8 instances as ‘high’ and o as ‘low’. Furthermore, based on this model performs very well on the ‘high’ class. There are some misclassifications between ‘low’ and ‘medium’ and between ‘medium’ and ‘high’ with ‘medium’, being the most frequently misclassified class.

V. Results Summary

The Hybrid CNN-LSTM model achieved test accuracy approximately 93.24% and a test loss of 0.1822. the confusion matrix and the performance metrics plot provide further details different classes of model performance. The plots indicate the model trained efficiently without significant overfitting within the 100 epochs, as the both training and validation metrics show similar trends in validation plot. The confusion matrix bar chart further details, highlighting a balanced performance focusing precision value and recall value with F1-score. Overall., the model appears well-suited for this classification problem on the provided dataset and achieved metrics.

VI. CONCLUSION

The Hybrid CNN-LSTM model accomplished test precision approximately 93.24% and a test loss of 0.1822. the confusion matrix and the performance metrics plot provide further details on the model's performance crossways the different classes. The training and validation plots indicate that the model trained effectively without significant overfitting within the 100 epochs, as the both training and validation metrics show similar trends. The confusion matrix bar chart further details the model's ability to correctly classify instances across different classes, highlighting a balanced performance in terms of precision, recall, and F1-score.

REFERENCES

[1] L. Syed, "Smart Agriculture using Ensemble Machine Learning Techniques in IoT Environment," *Procedia Comput. Sci.*, vol. 235, pp. 2269–2278, 2024, doi: 10.1016/j.procs.2024.04.215.

[2] R. K. Goel, C. S. Yadav, S. Vishnoi, and R. Rastogi, "Smart agriculture – Urgent need of the day in developing countries," *Sustain. Comput. Informatics Syst.*, vol. 30, no. December 2019, p. 100512, 2021, doi: 10.1016/j.suscom.2021.100512.

[3] H. Azadi, "Rethinking resilient agriculture: From Climate-Smart Agriculture to Vulnerable-Smart Agriculture," *J. Clean. Prod.*, vol. 319, no. January, p. 128602, 2021, doi: 10.1016/j.jclepro.2021.128602.

[4] J. A. Muñoz-Alegría, J. Núñez, R. Oyarzún, C. A. Chávez, J. L. Arumí, and L. Rodríguez-López, "A Bibliometric-Systematic Literature Review (B-SLR) of Machine Learning-Based Water Quality Prediction: Trends, Gaps, and Future Directions," *Water (Switzerland)*, vol. 17, no. 20, pp. 1–36, 2025, doi: 10.3390/w17202994.

[5] M. Padhiary, R. Kumar, and L. N. Sethi, "Navigating the Future of Agriculture: A Comprehensive Review of Automatic All-Terrain Vehicles in Precision Farming," *J. Inst. Eng. Ser. A*, vol. 105, no. 3, pp. 767–782, 2024, doi: 10.1007/s40030-024-00816-2.

[6] A. Theofilou, S. A. Nastis, M. Tsagris, S. Rodriguez-Perez, and K. Mattas, "Design and Implementation of a Scalable Data Warehouse for Agricultural Big Data," *Sustain.*, vol. 17, no. 8, pp. 1–19, 2025, doi: 10.3390/su17083727.

[7] M. Padhiary, D. Saha, R. Kumar, L. N. Sethi, and A. Kumar, "Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation," *Smart Agric. Technol.*, vol. 8, no. March, 2024, doi: 10.1016/j.atech.2024.100483.

[8] K. Dolaptsis, "A Hybrid LSTM Approach for Irrigation Scheduling in Maize Crop," *Agric.*, vol. 14, no. 2, pp. 1–25, 2024, doi: 10.3390/agriculture14020210.

[9] M. El Sakka, M. Ivanovici, L. Chaari, and J. Mothe, "A Review of CNN Applications in Smart Agriculture Using Multimodal Data," *Sensors*, vol. 25, no. 2, pp. 1–34, 2025, doi: 10.3390/s25020472.

[10] S. Ghazal, A. Munir, and W. S. Qureshi, "Computer vision in smart agriculture and precision farming: Techniques and applications," *Artif. Intell. Agric.*, vol. 13, pp. 64–83, 2024, doi: 10.1016/j.aiia.2024.06.004.

[11] R. Singh, A. Gehlot, S. Vaseem Akram, A. Kumar Thakur, D. Buddhi, and P. Kumar Das, "Forest 4.0: Digitalization of forest using the Internet of Things (IoT)," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 34, no. 8, pp. 5587–5601, 2022, doi: 10.1016/j.jksuci.2021.02.009.

[12] S. Seal, "Machine Learning for Toxicity Prediction Using Chemical Structures: Pillars for Success in the Real World," *Chem. Res. Toxicol.*, vol. 38, no. 5, pp. 759–807, 2025, doi: 10.1021/acs.chemrestox.5c00033.

[13] N. Y. Murad, T. Mahmood, A. R. M. Forkan, A. Morshed, P. P. Jayaraman, and M. S. Siddiqui, "Weed Detection Using Deep Learning: A Systematic Literature Review," *Sensors*, vol. 23, no. 7, pp. 1–45, 2023, doi: 10.3390/s23073670.

[14] C. Y. Tai, W. J. Wang, and Y. M. Huang, "Using Time-Series Generative Adversarial Networks to Synthesize Sensing Data for Pest Incidence Forecasting on Sustainable Agriculture," *Sustain.*, vol. 15, no. 10, 2023, doi: 10.3390/su15107834.

[15] L. Drees, "Data-driven crop growth simulation on time-varying generated images using multi-conditional generative adversarial networks," *Plant Methods*, vol. 20, no. 1, pp. 1–28, 2024, doi: 10.1186/s13007-024-01205-3.

[16] Y. Jung, "On-site applicable diagnostic fluorescent probe for fire blight bacteria," *iScience*, vol. 26, no. 4, p. 106557, 2023, doi: 10.1016/j.isci.2023.106557.

[17] M. Hudait and P. P. Patel, "Crop-type mapping and acreage estimation in smallholding plots using Sentinel-2 images and machine learning algorithms: Some comparisons," *Egypt. J. Remote Sens. Sp. Sci.*, vol. 25, no. 1, pp. 147–156, 2022, doi: 10.1016/j.ejrs.2022.01.004.

[18] S. Iqbal, A. Ayaz, M. Qabulio, M. S. Memon, and S. Nizamani, "A Deep Learning Based

Model for the Classification of Cotton Crop Disease," *Tech. Journal, Univ. Eng. Technol. Taxila, Pakistan ISSN1813-1786 2313-7770*, vol. 29, no. 1, pp. 61–68, 2024.

[19] G. Han, D. K. P. Asiedu, and K. E. Bennin, "Plant disease detection with generative adversarial networks," *Heliyon*, vol. 11, no. 7, p. e43002, 2025, doi: 10.1016/j.heliyon.2025.e43002.

[20] N. Bahrampour, M. Seifbarghy, and S. H. R. Pasandideh, *Supply chain management under VMI strategy using internet of things and smart contracts*, vol. 37, no. 5. Springer London, 2025. doi: 10.1007/s00521-024-10791-1.

[21] S. Bahoo, M. Cucculelli, X. Goga, and J. Mondolo, *Artificial intelligence in Finance: a comprehensive review through bibliometric and content analysis*, vol. 4, no. 2. Springer International Publishing, 2024. doi: 10.1007/s43546-023-00618-x.

[22] U. R. Shaikh, "A Review of Agro-Industry in IoT : Applications and Challenges," vol. 17, no. 1, pp. 28–33, 2019.

[23] Y. Xing, X. Zhang, and X. Wang, "Enhancing soil health and crop yields through water-fertilizer coupling technology," *Front. Sustain. Food Syst.*, vol. 8, no. November, pp. 1–23, 2024, doi: 10.3389/fsufs.2024.1494819.

[24] A. Kaur, D. P. Bhatt, and L. Raja, "Developing a Hybrid Irrigation System for Smart Agriculture Using IoT Sensors and Machine Learning in Sri Ganganagar, Rajasthan," *J. Sensors*, vol. 2024, 2024, doi: 10.1155/2024/6676907.

[25] V. Vitaskos, K. Demestichas, S. Karetsos, and C. Costopoulou, "Blockchain and Internet of Things Technologies for Food Traceability in Olive Oil Supply Chains," *Sensors*, vol. 24, no. 24, 2024, doi: 10.3390/s24248189.

[26] T. T. Rajapaksha, A. Alexander, L. Fernando, A. Than, and H. Le Nguyen, "Real-Time Weather Monitoring and IoT-Based Palmtop Device for Smart Agriculture," *SN Comput. Sci.*, vol. 3, no. 1, pp. 1–6, 2022, doi: 10.1007/s42979-021-00961-6.

[27] S. Sandeepkumar, K. J. Mohan, and K. Amarendra, "IOAT in Agricultural Research: Continuous Monitoring and Analysis of Demographic Data to Assess Cotton Crop Potential in Paddy Fields," *Int. J. Intell. Syst. Appl. Eng.*, vol. 12, no. 6, pp. 130–138, 2024.

[28] S. Faisal, M. P. L. Ooi, Y. C. Kuang, S. K. Abeysekera, and D. Fletcher, "An Overview of Integrating Deep Learning Methods with Close-Range Hyperspectral Imaging for Agriculture," *IEEE Access*, vol. 13, no. April, pp. 120257–120276, 2025, doi: 10.1109/ACCESS.2025.3587226.

[29] C. Nguyen, V. Sagan, M. Maimaitiyiming, M. Maimaitijiang, S. Bhadra, and M. T. Kwasniewski, "Early detection of plant viral disease using hyperspectral imaging and deep learning," *Sensors (Switzerland)*, vol. 21, no. 3, pp. 1–23, 2021, doi: 10.3390/s21030742.

[30] A. Kaur, G. Singh, V. Kukreja, S. Sharma, S. Singh, and B. Yoon, "Adaptation of IoT with Blockchain in Food Supply Chain Management: An Analysis-Based Review in Development, Benefits and Potential Applications," *Sensors*, vol. 22, no. 21, 2022, doi: 10.3390/s22218174.

[31] H. S. Bhaskaran, M. Gordon, and S. Neethirajan, "Development of a cloud-based IoT system for livestock health monitoring using AWS and python," *Smart Agric. Technol.*, vol. 9, no. August, p. 100524, 2024, doi: 10.1016/j.atech.2024.100524.

[32] J. A. Wani, S. Sharma, M. Muzamil, S. Ahmed, S. Sharma, and S. Singh, *Machine Learning and Deep Learning Based Computational Techniques in Automatic Agricultural Diseases Detection: Methodologies, Applications, and Challenges*, vol. 29, no. 1. Springer Netherlands, 2022. doi: 10.1007/s11831-021-09588-5.

[33] M. A. Tunc, E. Gures, and I. Shayea, "A Survey on IoT Smart Healthcare: Emerging Technologies, Applications, Challenges, and Future Trends," pp. 1–15, 2021, [Online]. Available: http://arxiv.org/abs/2109.02042

[34] A. Abdusalomov, "AI-Driven UAV Surveillance for Agricultural Fire Safety," *Fire*, vol. 8, no. 4, pp. 1–18, 2025, doi: 10.3390/fire8040142.

[35] F. Gatta, F. Giampaolo, D. Chiaro, and F. Piccialli, "Predictive maintenance for offshore oil wells by means of deep learning features extraction," *Expert Syst.*, vol. 41, no. 2, pp. 1–13, 2024, doi: 10.1111/exsy.13128.

[36] A. Gupta and P. Nahar, "Classification and yield prediction in smart agriculture system using IoT," *J. Ambient Intell. Humaniz. Comput.*, vol. 14, no. 8, pp. 10235–10244, 2023, doi: 10.1007/s12652-021-03685-w.

[37] D. S. Joseph, P. M. Pawar, and R. Pramanik, "Intelligent plant disease diagnosis using convolutional neural network: a review," *Multimed. Tools Appl.*, vol. 82, no. 14, pp. 21415–21481, 2023, doi: 10.1007/s11042-022-14004-6.