Library Progress International *Print version ISSN 0970 1052*
Vol.44 No. 3, Jul-Dec 2024: P.13401-13411 *Online version ISSN 2320 317X*

Original Article *Available online at www.bpasjournals.com*

Convolutional Autoencoder Network with Multi-Instance Attention Network Based Weather Condition-Based Crop Identification in IOT

Dr. R. Srinivasan[1], V. Vaithianathan[2], Dr. J. Venkatesh[3], Dr. Smitha. P. S[4] and R. Pradeepa[5]

[1]Professor, Department of Computer science and Engineering, Vel Tech Rangarajan Dr Sagunthala R & D institute of science and technology, Avadi, Chennai, India (0000-0002-5348-0170).
[2]Associate Professor, Department of Electronics and Communication Engineering, Sri Sivasubramaniya Nadar College of Engineering, Kalavakkam, Chennai – 603110 (0000-0002-5482-4019)
[3]Professor, Department of Computer Science and Engineering, Chennai Institute of Technology, Kundrathur, Chennai, India (0000-0002-4259-130X)
[4]Associate Professor, Department of Computer science and Engineering, Velammal Engineering College, Chennai
[5]Assistant Professor, Department of Information Technology, Sona College of technology, Salem, India
[1]srinivasanrajkumar28@gmail.com, [2]vaithianathanv@ssn.edu.in, [3]venkateshj@citchennai.net, [4]Smitha.p@velammal.edu.in and [5]pradeepagandhi@gmail.com

How to cite this article: R. Srinivasan, V. Vaithianathan, J. Venkatesh, Smitha. P. S, R. Pradeepa (2024). Convolutional Autoencoder Network with Multi-Instance Attention Network Based Weather Condition-Based Crop Identification in IOT *Library Progress International,* 44(3), 13401-13411.

ABSTRACT
In the field of precision agriculture, appropriate crop recommendation systems play a critical role in maximizing crop production and optimizing resource utilization. Weather condition depends on a novel approach to crop identification introduced by this research using an Internet of Things (IoT) framework with convolutional autoencoder network multi instance attention network (CAN-MIAN). This requires detailed preprocessing which also includes noise filtering, removal of missing values and duplicated data from the recommended crop dataset that includes information about rainfall, weather, agriculture, soil and fertilizers in India. Using Hybrid Crested Porcupine Zebra optimization Algorithm for feature selection will improve model accuracy. The Enhanced Sparrow Search Algorithm tuned CAN-MIAN is then used for training to enable the system predict the best crops for specific cases based on environmental parameters. As such, it provides an accurate and reliable forecast generating tools useful in agricultural decision making processes. Also, it facilitates ease in data processing flow while embedding advanced optimization algorithms into weather driven cropping pattern design through minimizing energy wastages inherent in broad acre practices. The proposed method attains higher accuracy as 97.1%.

Keywords: Data preprocessing, Crested Porcupine Optimization, Zebra Optimization, Convolutional Autoencoder Network with Multi-instance Attention Network

1. INTRODUCTION

In India, agriculture is the main source of income for most people and is crucial to the growth of local livelihoods. However, even though information technology is used extensively in other spheres of society, like manufacturing, pollution control, and other areas of life, conventional agriculture production still primarily depends on human labor [1-3]. The IoT is used extensively in agriculture, as demonstrated by the fact that it is helpful in monitoring soil information in suitable locations and assisting in the use of conventional irrigation systems, among other things.

IoTs are essential to the concept of smart agriculture meanwhile they collect and monitor data on agricultural grounds of interest for a variety of uses. In order to eliminate water waste, low soil fertility, fertilizer misuse, and sicknesses, smart agriculture requires major efforts to implement precision irrigation, fertilizers, and pesticides based on the crop development model and WSNs in agriculture. Wireless communication of gathered soil data to the sink node is possible between IoT sensor nodes in fields [4-6]. Information on temperature, humidity, soil moisture content, and wind speed using IoTs. Farmers working throughout the entire growing season receive a lower wage due to mediators' ignorance about crop yield and productivity (agents for bargaining). If farmers received the right guidance or assistance about crop cultivation, yield pricing, and crop selling, their labor-intensive work would not be in vain. If not, crop yield will decline, which will have an impact on the national economy[7-9]. Therefore, the nation's economy will significantly grow if the government offers suitable support for these skills in addition to the traditional way of operating agriculture [10-12].

Farming is one of the most important jobs done in India. It is the most diverse economic sector and essential to the development of the nation. An extra 60% of the land in the nation is used for agriculture in order to feed the 1.3 billion people that live there. Thus, it is imperative to apply modern agricultural techniques [13-15]. This would help the farmers in our country become financially successful. Crop and yield estimates have historically been established based on farmers' past experience in a particular area. They don't know enough about the nutrients found in the soil, like potassium, phosphate, and nitrogen [16-18]. For their property alone, they would choose the more mature, well-established, or stylish crops in the neighborhood. Production is declining as a result of the current situation, which also causes soil pollution and damage to the top layer as a result of inadequate nutrient treatment and lack of crop rotation. Additionally, a few of crop prediction methods take longer to produce results and don't offer enough accuracy[19,21]. This manuscript addresses all of these issues by proposing an CAN-MIAN system to accurately predict various crops in a short amount of processing time. The main contributions of this research are;

- Introduction of the CAN-MIAN for accurate crop recommendation, integrating advanced neural network architectures for enhanced weather condition-based predictions.
- Implementation of comprehensive data preprocessing techniques to handle noise, missing values, and redundancy in a diverse dataset that includes rainfall, weather, soil, agriculture, and fertilizer information.
- Application of the Hybrid Crested Porcupine Zebra Optimization Algorithm for effective feature selection, improving the model's accuracy by identifying the most relevant features for crop recommendation.
- Utilization of the Enhanced Sparrow Search Algorithm to optimize the CAN-MIAN model, resulting in significant gains in prediction accuracy and reliability for targeted agricultural practices.

2. LITERATURE SURVEY

For crop prediction depend on climatic and soil circumstances, Venkatanaresh M. and Kullayamma I. [20] proposed a deep learning based concurrent excited gated recurrent unit in 2024. In this study, a unique deep learning (DL) approach for crop recommendation based on soil, fertilizers, and climate is presented. Real-time gathered Maharashtra datasets that include both soil and climate factors, as well as publicly accessible Kaggle datasets, are utilized to test and train the suggested approach. To dependably propose crops, a new Concurrent Excited Gated Recurrent Unit based DL technique is first trained using data from the dataset. Furthermore, the hunter-prey optimization (HPO) technique, a meta-heuristic algorithm, is presented to adjust the parameters of the suggested network model.

In 2023, Apat SK et al. [22] suggested a machine learning-based artificial intelligence-based crop recommendation system. According to our research, precision agriculture benefits from the AI system in terms of overall crop harvest quality and accuracy. Industry 4.0, the research feature selection, offers one approach, such as a recommendation system, by utilizing AI and a group of machine learning procedures. The labeled data set utilized in this study was taken from Kaggle. It has eight features in total, seven independent variables, temperature, humidity, pH, rainfall, N, P, and K. To get better outcomes, the SMOTE data balancing approach is then used. The authors also employed optimization approaches to fine-tune the smart factories' performance.

In 2021, Gosai D et al. [23] suggested a machine learning-based crop recommendation system. By utilizing sensors, the proposed IoT and ML system enables soil testing over the dimension and statement of soil properties. This scheme uses various sensors, including soil moisture, soil temperature, pH, and NPK nutrients, to monitor the soil's temperature, humidity, soil moisture, pH, and NPK levels. The microcontroller stores the data that these sensors detect, and machine learning methods such as random forest are used to analyze the data and provide recommendations for the growth of a suitable crop. Convolutional neural networks are the main tool used in this project's method to define whether or not a plant is disease-prone.

CropCast: Harvesting the future with interfused ML and advanced stacking ensemble for accurate crop prediction in 2024 is a proposal put forth by Raju C et al. [24] The main objective is to create the IML-ASE method, which will use data on soil, agricultural, and environmental factors in AE zones to assist farmers in choosing crops based on expertise. Data collection from crop recommendation datasets, preprocessing, and feeding into the suggested model are the steps in the process. The advanced stacking model is composed of three layers: the base learners, or first layer, use different ensemble strategies, while the meta-learner, or second layer, acts as the fine learner. With the help of AE zone features, this research attempts to alleviate the problems associated with contemporary agriculture by giving farmers more precise crop predictions.

2.1 Problem statement

Optimizing resource allocation and crop yields remains a major challenge in precision agriculture, especially under ever-changing environmental conditions. Conventional crop recommendation systems typically fail to precisely predict which crops suit the given difficult weather and soil variables. This research uses a unique CAN-MIAN method, which combines CAN-MIAN, within an IoT framework. The objective is to make a strong system that improves the accuracy of forecasting by handling large datasets such as climate, soil, field information among others in the most appropriate manner possible through applying advanced optimization techniques that customizes recommendations for unique environmental circumstances.

3. PROPOSED METHODOLOGY

This study presents a unique method for crop identification based on weather conditions using an Internet of Things (IoT) framework and a Convolutional Autoencoder Network with Multi-instance Attention Network (CAN-MIAN). The first step of the procedure involves a thorough preparation of the data to address problems like noise, missing values, and redundancy in the crop recommendation dataset. This dataset includes information about India's rainfall, weather, soil, agriculture, and fertilizer.

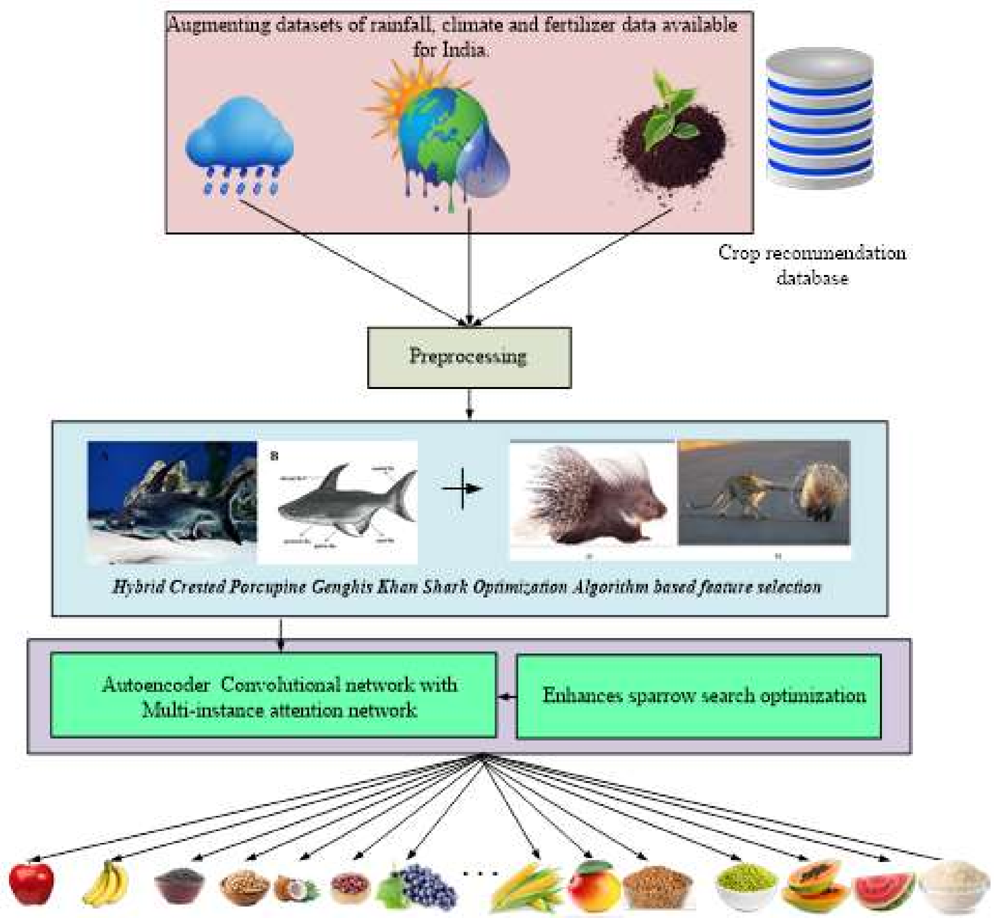

Figure 1: Framework of proposed architecture

To improve model accuracy, a Hybrid Crested Porcupine Zebra Optimization Algorithm is used for feature selection. The Enhanced Sparrow Search Algorithm is then used to optimize the CAN-MIAN model, which is then taught to forecast appropriate crops depending on environmental factors. The suggested system offers a strong tool for agricultural decision-making and shows notable increases in forecast accuracy and reliability. Figure 1, shows the framework of introduced approach.

3.1 Input acquisition

The crop recommendation database was created by adding information about soil, agriculture, rainfall, weather, and fertilizer that was accessible for India. The descriptions of the different aspects of the dataset are given in Table 1.

Data	Explanation
Rainfall	In millimeter
pH	Of soil
Humidity	In percentage
Temperature	In degree Celsius
K	Potassium
P	Phosphorous
N	Nitrogen

3.2 Preprocessing

Preprocessing the soil, environment, and agricultural inputs from the crop recommendation database is necessary before training the model. The unsuitable, noisy, and missing data from the data sources significantly affect how effectively machine learning models perform, which is totally dependent on data preprocessing. The initial step in data preprocessing is reading the attained database; data filtering follows. To increase accuracy, redundant traits and inconsistent data are filtered out of the dataset. After data filtering, the database will be split into testing and training sets. The suggested crop forecast model is provided with this pre-processed output.

3.3 Hybrid Crested Porcupine Zebra optimization algorithm based feature selection

To choose pertinent features from the preprocessed data in this study, an optimization technique known as the Hybrid Crested Porcupine Zebra is employed. By combining the advantages of several optimization techniques, the Hybrid Crested Porcupine Zebra optimization algorithm improves feature selection. This results in a more precise and effective identification of pertinent features, which boosts model performance, lowers error rates, and prevents overfitting.

3.3.1 Crested Porcupine Optimizer

Motivated by the varied protective behaviors of crested porcupines (CP), a technique is proposed for accurately optimizing various optimization problems, especially those involving enormous amounts of data. The four defense mechanisms used by the crowned porcupine range from the least to the most aggressive: sight, sound, smell, and bodily assault.

3.3.2 Zebra optimization algorithm

Zebras are equine animals that are indigenous to eastern and southern Africa. This animal is highly recognized for having black and white stripes all over its body. These stripes, which are frequently present in a vertical pattern on the body and neck, effectively shield zebras from predators and keep flying insects away. Their requirements and details are as follows: Their body length is 210-300 cm, their tail is lengthy (38-75 cm), and their shoulder height is 110-160 cm. They weigh between 175-250 kg. The zebra is a hefty mammal with long, slender legs that allow it to travel fast when necessary. Similar to wild horses, zebras have a long neck, one toe on each foot, and a head structure that makes it easier for them to eat the grass beneath the surface. Foraging and protecting against predators are the two most important behavioral patterns that zebras display in their social interactions.

3.3.3 Initialization & Random generation

The parameters of the Zebra and Crested Porcupine Optimizer algorithms are first initialized, and after that, they are created at random.

3.3.4 Fitness function

Equation (1) illustrates the fitness function of the newly suggested optimization approach for hybrid crested porcupine zebras.

$$Fit_{Fun} = Z * Err + (1 - Y)\frac{\sum_i \theta_i}{n} \tag{1}$$

where n is the entire feature count in the database, Fit_{Fun} is the fitness function assumed a vector sized by Z elements representing unselected / selected features, Err is the classifier error rate, and Y is a constant to the number of features selected.

3.3.5 Exploration

Based on its defensive behavior $\vec{X}_I^{T+1}$, the CP has two protection strategies: the sight strategy and the sound strategy when the predator is far away. These strategies refer to an exploratory search aimed at a survey of different places (worldwide). Unlike when they employ smell and physical attack, the CPs $\vec{C}$ can utilize sight and sound to scare away a predator when it gets very close. In the second method, the CP scare the predator by using the sound strategy. The predator's voice grows stronger as it approaches the porcupine. An algebraic simulation of this behavior is proposed in equation (2).

$$\vec{E}_I^{T+1} = \left(1-\overrightarrow{V1}\right)\times \overrightarrow{E_I^T} + \overrightarrow{V1}\times\left(\vec{C} + R3\left(\overrightarrow{E_{R1}^T} - \overrightarrow{E_{R2}^T}\right)\right) \tag{2}$$

where $R1$ and $R2$ are two random integers between 0 and 1 and is a randomly generated number between $[1,n]$ and $\overrightarrow{U1}$ is the upper limit.

3.3.6 Exploitation

The second phase updates the location of members of the ZOA population in the search space by utilizing models of the zebra's defense mechanism against predator attacks. While lions are zebras' primary predators, cheetahs, leopards, wild dogs, brown hyenas, and spotted hyenas are all potential threats to these species. As zebras approach the river, they encounter crocodiles as well as other predators. Zebras have different protection strategies according to the kind of predator they face. The zebra defends itself from lion attacks by making zigzag escape routes and occasionally bending sideways. Zebras are more aggressive in order to confuse and frighten smaller predators such as hyenas and dogs.

3.5 Convolutional Autoencoder network with Multi-instance attention network (CAN-MIAN)

Multi-instance Attention Network is designed to handle multiple instances or variations of data effectively by focusing on the most relevant parts. In crop identification, Multi-instance Attention Network could help prioritize critical features or data points, enhancing the model's ability to discern between different crop types based on subtle patterns or environmental conditions. CAE is a type of neural network that learns efficient codings by compressing and then reconstructing input data. In the context of crop identification, the CAE can extract important features from agricultural images or sensor data, reducing dimensionality while preserving key information. Utilizing the Enhanced Sparrow Search Algorithm the performance of CAN-MIAN is improced by tuning hyperparameters and optimizing network parameters for better accuracy and efficiency.The architecture of **CAN**-MIAN is shown in figure 2.

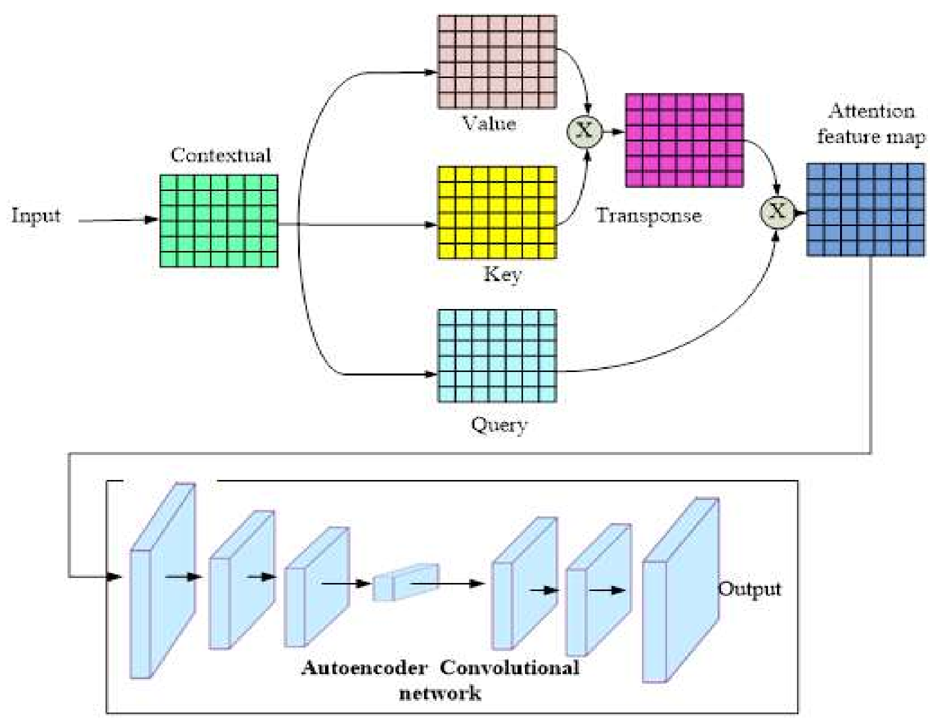

Figure 2: Architecture of **CAN-**MIAN

3.5.1 Multi-instance attention network

The self-attention mechanism has shown to be a successful model in the processing of images and natural language. A structure that is an extension of self-attention, multi-head self-attention has been successfully used to extract features of distinct views included in input values. Each head of the structure learns features of different subspaces. Combining representations from all subspaces can improve the multivariate feature information present in the input signal since different subspace representations concentrate on distinct information. Assume that x 2 RN, where N is the feature dimension, represents the features of the previous hidden layer. To calculate the attention map, the head of each feature $Y_{T,I,J}$ is converted into three feature types: time , sensor¸ and batch. Each of the three instance-based features acts as a header in the computation of the attention score. $b^{1/4}$ and $(W_a)$and (W_b) are the weights of the sensor and batch instances, respectively which is given by equation (3).

$$Y_{T,I,J} = \frac{EXP(W_a)}{\sum_{I=1}^{N} EXP(W_a)} \bullet W_a = U(W_b)^T T(W_a)$$

(3)

where T is the preceding layer's key value.

3.5.2 Convolutional Autoencoder network

An autoencoder that extends the basic structure of fully linked layers to convolution layers is called a convolutional autoencoder.In a basic autoencoder, the input layer has the same size as the output layers; however, the decoder's network transforms to convolutional layers, and then to transposed convolutional layers. The hyper-parameters (kernelsize, stride, and padding) for every convolution layer in use are listed in Table 1.

Table 2: Layers utilized in the convolutional autoencoder

Layer type	Window size	Padding	Sride
Trans ConV	3	1	1
Trans ConV	2	1	2
Trans ConV	3	1	2
Trans ConV	5	1	2
Pool(MAX)	2	1	1
ConV	3	1	1
Pool(MAX)	2	1	1
ConV	3	1	1
Pool(MAX)	2	1	1
ConV	3	1	1

3.5.3 Enhanced sparrow search algorithm

The basic SSA's preliminary population is generated in a pseudo-random manner, that may cause the primary individuals to accumulate and the population to be distributed unevenly. If the initial population can be generated more uniformly and randomly with targeted strategies, the quality of the first solution can be significantly enhanced and the convergence of the algorithm can be augmented. The original expression for the circle chaotic mapping is given in equation (4):

$$R_{i+1} = \mathrm{mod}\left(A_i - \left(\frac{Q}{2\pi}\right)\sin(2\pi A),1 \right)$$

(4)

In a quantum space, the smallest information unit is called a quantum bit Q. Quantum bits come in three varieties: single, double, and triple qubits. Equation (5) gives the fitness function.

$$Fitness\ Function = Min(W_a + W_b)$$

(5)

In this study, a single qubit was utilized. In quantum multiplication theory, the 2 fundamental states of a qubit, 0 and 1, represent the basic storage unit. The explanation for these states can be found in equation (6):

$$|\Phi\rangle = Y|0\rangle + |Z\rangle$$

(6)

where Y denotes the quantum state of a super-position and Z represents the profusions of the likelihood of being in one of two states, respectively. The algorithm continues to repeat this phase until either the criteria time Iteration $F = F + 1$ is reached or the termination condition is fulfilled [22].

4. RESULTS AND DISCUSSIONS

The crop recommendation dataset includes environmental, agricultural, and soil data. The Python library used an advanced stacking ensemble model of crop prediction technique to train and evaluate the integrated machine learning approach.

4.1 Dataset description

These days, precision agriculture is popular. It assists farmers in making well-informed decisions on their farming approach. I'm going to show you a dataset that will let you create a prediction model that will tell you which crops, given a number of criteria, would be most suited to grow on a specific farm. The rainfall, climate, and fertilizer data sets for India were supplemented to create this dataset (https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset).

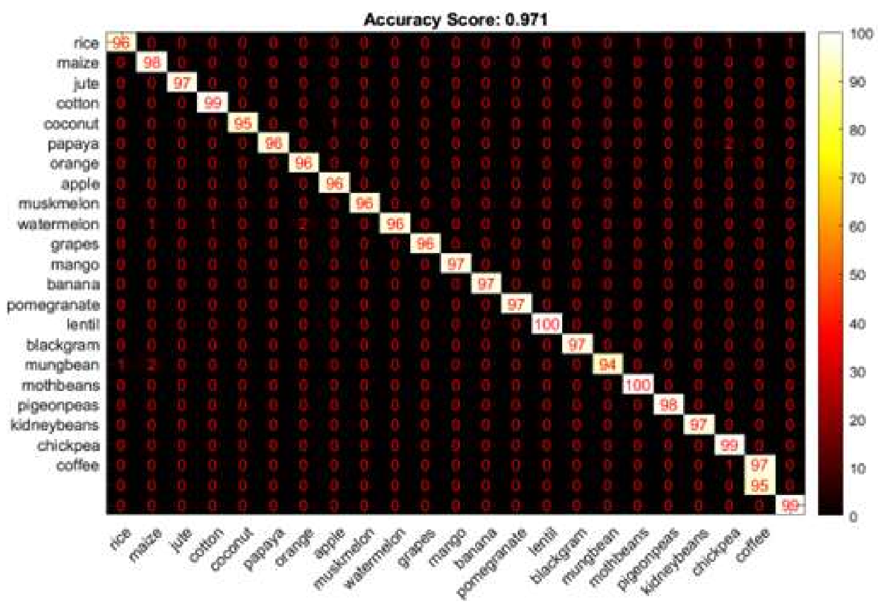

Figure 3: Confusion matrix

The confusion matrix, which evaluates the effectiveness of the suggested introduction model, is shown in Figure 3. The predicted labels are indicated by rows in this matrix, and the actual labels are indicated by columns. The presented model predicts different crop types with an exceptional overall accuracy of 0.971, according to the confusion matrix. This high accuracy demonstrates how well the model distinguishes between various crops, demonstrating its dependability and robustness in real-world settings. The confusion matrix offers important information into the model's classification performance and its potential for accurate crop selection by precisely matching expected and actual labels. Figure 4 (a) and (b) shows the training and testing accuracy and loss curves.

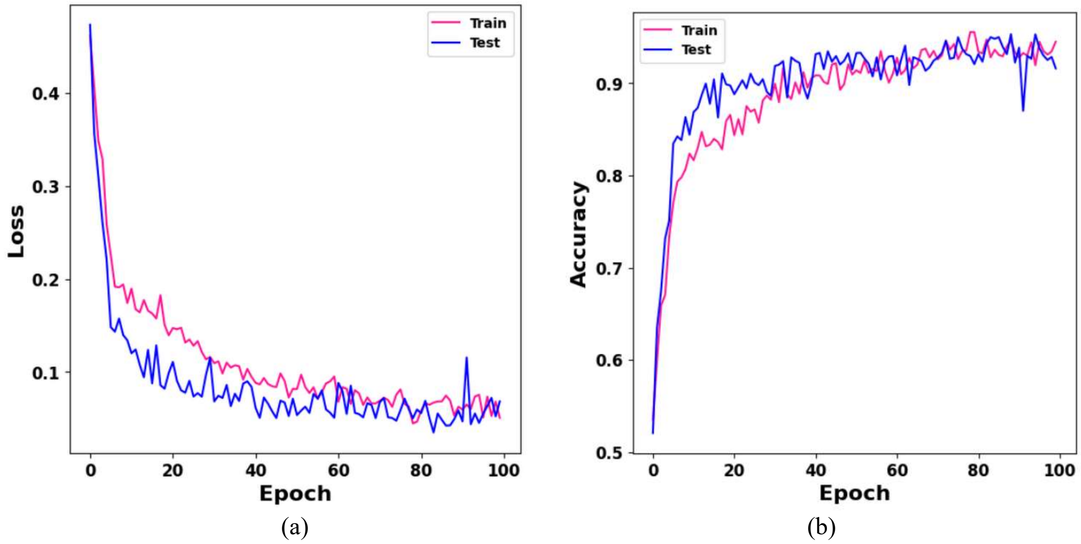

Figure 4: (a) Training and testing loss and (b) training and testing accuracy

The comparative analysis of different crop recommendation techniques highlights the superior performance of the proposed CAN-MIAN is shown in table 3. This model excels across all key performance metrics: accuracy, precision, sensitivity, specificity, and F1-score. Achieving an impressive accuracy of 97.1%, CAN-MIAN demonstrates its exceptional ability to make correct predictions, outperforming other techniques significantly.

Table 3: Performance analysis of proposed approach

Technique	Accuracy(%)	Precision(%)	Sensitivity(%)	Specificity(%)	F1-score(%)
CAN-MIAN(Proposed)	97.1	99.6	99.7	99.6	99.6
IML-ASE	95	94	93	94	92.5
SMOTE	84	74	75	76	74.5
HPO	83	85	86	87	85.5

The model's precision of 99.6% means that it has a very low rate of false positives, thus ensuring that the recommended crops are highly relevant and minimizing wrong suggestions. Sensitivity is also extraordinarily high at 99.7%, which shows that CAN-MIAN is good at detecting true positives, or appropriate crops, with relatively few missed opportunities. The model's specificity is 99.6%, meaning that it correctly excludes unsuitable crops and hence further proving its accuracy and reliability. Moreover, the F1-score at a level of 99.6% implies its overall robustness and efficacy of the CAN-MIAN model. On the other hand, IML-ASE exhibits strong performance but still lags behind CAN-MIAN in all measures of its performance levels. For example, IML-ASE has an accuracy level of 95%, precision level – 94%, sensitivity – 93%, and specificity – 94%. However, this method scored a relatively lower F1-score (92.5%) reflecting a balanced score card approach. Nonetheless, SMOTE with an accuracy rate of 84%; precision rate – 74%; recall rate -75%; and specificity rate –76% does not make significant strides towards predicting suitable crops as shown by its lower performance metrics. It further has an F1-score standing at about 74.5% which while can be helpful reveals less confidence compared to more advanced models than advanced ones do HPO, with an accuracy of 83%, precision of 85%, sensitivity of 86%, and specificity of 87%, shows moderate performance, slightly better than SMOTE but still less effective than CAN-MIAN and IML-ASE. The F1-score of 85.5% suggests that while HPO provides a reasonable balance between precision and sensitivity, it does not reach the high standards set by the CAN-MIAN model. Overall, the CAN-MIAN model stands out as the most effective approach for crop recommendation, demonstrating superior performance across all evaluated metrics. This indicates that the advanced techniques and optimizations employed in CAN-MIAN provide a substantial improvement over traditional methods, making it a highly suitable choice for accurate and reliable crop prediction in precision agriculture.

Table 4: Error rate analysis of proposed approach

Technique	MSE	RMSE	MAE
CAN-MIAN(Proposed)	1.32	0.89	0.18
IML-ASE	2.73	1.65	0.23
SMOTE	3.37	2.56	1.21
HPO	3.45	2.64	2.22

The table 4, evaluates different methods based on Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Of all methods, CAN-MIAN (Proposed) demonstrates the best performance with its low MSE (1.32), RMSE (0.89), and MAE (0.18), meaning it has high accuracy and a few prediction errors. IML-ASE showed bigger errors with an RMSE of 1.65 and MAE of 0.23, while MSE was at 2.73. On the other side, SMOTE has highest MSE(3.37) and RMSE(2.56) but moderate MAE(1.21); a reflection of poor accuracy here in this technique HPO registers the worst errors across all metrics such as MSE (3.45), RMSE(2.64) and MAE(2.22). This makes it being the least accurate method among others considered in this study.

5. CONCLUSION

In conclusion, this research introduces a cutting-edge crop recommendation system that leverages a CAN-MIAN within an IoT framework for precise weather condition-based crop identification. By meticulously addressing data preprocessing challenges and employing the Hybrid Crested Porcupine Zebra Optimization Algorithm for feature selection, the system significantly enhances prediction accuracy. The CAN-MIAN model, optimized through the Enhanced Sparrow Search Algorithm, demonstrates marked improvements in both accuracy and reliability, making it a valuable tool for agricultural decision-making. Looking ahead, future work could focus on expanding the model's applicability to a broader range of crops and environmental conditions, integrating real-time data processing capabilities, and exploring additional optimization algorithms. Furthermore, incorporating feedback mechanisms from actual field deployments could refine the model's predictions and adapt to changing agricultural trends, ultimately contributing to more sustainable and efficient farming practices.

REFERENCES

1. Thilakarathne NN, Bakar MS, Abas PE, Yassin H. A cloud enabled crop recommendation platform for machine learning-driven precision farming. Sensors. 2022 Aug 22;22(16):6299.
2. Balaji Singaram, Lakshmi. B, Dr. M. Preetha, V. K. Ramya Bharathi, Dr. S. Muthumarilakshmi, Rakesh Kumar Giri (2024), "A Smart IoT-Based Fire Detection and Machine Learning Based Control System for Advancing Fire Safety", Nanotechnology Perceptions, ISSN: 1660-6795, Vol.20, Issue S5, page No-229-244.
3. Dr. A. Deepa, Vidhyashree B, S. R. Venkataraman, Gomathi C, Dr. G. Madasamy Raja, Dr. M. Preetha (2024), "A Comprehensive IoT-Based Automation System for Enhanced Productivity and Sustainability for Advancing Farming Efficiency", Nanotechnology Perceptions, ISSN: 1660-6795, Vol.20, Issue S5, page No-215-228.
4. Elbeltagi A, Deng J, Wang K, Malik A, Maroufpoor S. Modeling long-term dynamics of crop evapotranspiration using deep learning in a semi-arid environment. Agricultural Water Management. 2020 Nov 1;241:106334.
5. Anami BS, Malvade NN, Palaiah S. Deep learning approach for recognition and classification of yield affecting paddy crop stresses using field images. Artificial intelligence in agriculture. 2020 Jan 1;4:12-20.
6. Srinivasan, S, M.S. Vinmathi, S.N. Sivaraj, A. Karthikayen, C. Alakesan, & Preetha, M. (2024), "A Novel Approach Integrating IoT and WSN with Predictive Modeling and Optimization for Enhancing Efficiency and Sustainability in Smart Cities", Journal of Electrical Systems (IES), ISSN: 1112-5209, Vol.20, Issue 4, page No-2228-2237.
7. Turkoglu MO, D'Aronco S, Perich G, Liebisch F, Streit C, Schindler K, Wegner JD. Crop mapping from image time series: Deep learning with multi-scale label hierarchies. Remote Sensing of Environment. 2021 Oct 1;264:112603.
8. S. Devikala, Rabi.J, V.P.Murugan, J.S. Christy Mano Raj, K. Mohanasundaram, K Sivakumar, "Development of fuzzy logic controller in Automatic Vehicle Navigation using IOT.," Journal of Electrical Systems, https://doi.org/10.52783/jes.1254 ISSN 1112-5209 2024, Vol: 20, 3s, 114-121.

9. Dr.M.Preetha, P.Bhuvaneswari, Ilakkiya.M, Karthigha.P "Deterrence of Accident in Vehicles Using IOT", International Journal for Research in Applied Science & Engineering Technology, Vol.7, Issue III, March 2019. ISSN 2321-9653.

10. N. Mohana Priya, G. Amudha, M. Dhurgadevi, N. Malathi, K. Balakrishnan & Preetha, M. (2024), "IoT and Machine Learning based Precision Agriculture through the Integration of Wireless Sensor Networks", Journal of Electrical Systems (IES), ISSN: 1112-5209, Vol.20, Issue 4, page No- 2292-2299.

11. Dasgupta I, Saha J, Venkatasubbu P, Ramasubramanian P. AI crop predictor and weed detector using wireless technologies: a smart application for farmers. Arabian Journal for Science and Engineering. 2020 Dec;45:11115-27.

12. Balaji Singaram, M.S.Vinmathi, Dr.H.B.Michael Rajan, Jeyamohan H, T. Manikandan, "Data-Driven Estimation of Lithium-Ion Battery State-of-Health Prediction Approach Using Machine Learning Algorithm for Enhanced Battery Management Systems", Nanotechnology Perceptions, ISSN 1660-6795 2024, Vol: 20, 7s, 93-103.

13. Zhou J, Li J, Wang C, Wu H, Zhao C, Teng G. Crop disease identification and interpretation method based on multimodal deep learning. Computers and Electronics in Agriculture. 2021 Oct 1;189:106408.

14. Dr M Preetha, Akshaya M, Arthima A, Mr.Akhilesh Kumar Pahade, Nusratova Khamida, (2023), "A ZIGBEE garbage bin monitoring system with IoT", E3S Web of Conferences International Conference on Newer Engineering Concepts and Technology (ICONNECT-2023), eISSN : 2267-1242, Article No.04052, Vol.399, 12th July 2023.

15. Swaminathan B, Palani S, Vairavasundaram S, Kotecha K, Kumar V. IoT-driven artificial intelligence technique for fertilizer recommendation model. IEEE Consumer Electronics Magazine. 2022 Feb 16;12(2):109-17.

16. Garg G, Gupta S, Mishra P, Vidyarthi A, Singh A, Ali A. CROPCARE: an intelligent real-time sustainable IoT system for crop disease detection using mobile vision. IEEE Internet of Things Journal. 2021 Sep 1;10(4):2840-51.

17. Bali N, Singla A. Deep learning based wheat crop yield prediction model in Punjab region of North India. Applied Artificial Intelligence. 2021 Dec 15;35(15):1304-28.

18. Bakthavatchalam K, Karthik B, Thiruvengadam V, Muthal S, Jose D, Kotecha K, Varadarajan V. IoT framework for measurement and precision agriculture: predicting the crop using machine learning algorithms. Technologies. 2022 Jan 20;10(1):13.

19. E.S. Phalguna Krishna, N. Praveena, I. Manju, N. Malathi, K. Balakrishnan, & Preetha, M. (2024), "IoT-Enabled Wireless Sensor Networks and Geospatial Technology for Urban Infrastructure Management", Journal of Electrical Systems (IES), ISSN: 1112-5209, Vol.20, Issue 4, page No- 2248-2256.

20. Venkatanaresh M, Kullayamma I. Deep learning based concurrent excited gated recurrent unit for crop recommendation based on soil and climatic conditions. Multimedia Tools and Applications. 2024 Jan 12:1-30.

21. Dr.M.Preetha, Balaji Singaram, Dr.I. Manju, B.Hemalatha, P. Bhuvaneswari "Machine Learning in Breast Cancer Treatment for Enhanced Outcomes with Regional Inductive Moderate Hyperthermia and Neoadjuvant Chemotherapy" Nanotechnology Perceptions, ISSN 1660-6795 2024, Vol: 20, 5s, 245-259.

22. Apat SK, Mishra J, Raju KS, Padhy N. An artificial intelligence-based crop recommendation system using machine learning.

23. Gosai D, Raval C, Nayak R, Jayswal H, Patel A. Crop recommendation system using machine learning. International Journal of Scientific Research in Computer Science, Engineering and Information Technology. 2021 Jun;7(3):558-69.

24. Raju C, Ashoka DV, BV AP. CropCast: Harvesting the future with interfused machine learning and advanced stacking ensemble for precise crop prediction. Kuwait Journal of Science. 2024 Jan 1;51(1):100160.