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MRESGAT: MULTI-HEAD RESIDUAL DILATED CONVOLUTION ASSISTED GATED UNIT FRAMEWORK FOR CROP YIELD PREDICTION

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Abstract. The importance of predicting crop yields has increased due to growing concerns of surrounding food security. Early forecasting of crop yields holds a pivotal role in avoiding starvations by estimating the food supply available for the expanding global population. Several Deep Learning (DL) and Machine Learning (ML) techniques are involved to develop effective and accurate crop yield prediction model. Nevertheless, existing models faces some limitations such as less accuracy, high error rate because of noisy data, high training time and extracted less effective features for prediction. To overcome these issues, the novel DL methodology is introduced for attaining high accurate crop yield prediction. Initially, the soil, weather and other resources big data are collected from the various agriculture field. In data collection phase, the input data of larger size are stored in the Hadoop platform for the purpose of storing as well as processing the entire data in a distributed manner. The data are pre-processed through the utilization of Missing value imputation and z-score based data normalization. From the pre-processed data, the optimal features are considered using Integrated Correlation Random recursive elimination (InCorRe) approach. Based on the previous soil and weather information, the suitable yield of crops can be predicted using Multi head Residual dilated convolution assisted gated unit (MResGat) model. Finally, the losses of the network model can be optimized using African vulture optimization algorithm (AVO). The proposed method is evaluated using the several performance metrics, which achieved 0.023% of MSE value and 0.036% of MAE values.

Key words: Deep Learning, Crop yield prediction, Hadoop platform, Multi head attention, Residual dilated convolution assisted gated unit, African vulture optimization and Integrated Correlation Random recursive elimination.

1. Introduction. Development minded formers have the experienced to predicting the crop yield with precision before introducing the computer technology. In order to achieve this, the farmers collected complete records of their fields during the growing and harvest seasons. Then, using their gathered knowledge and experience, they tried to determine the best plan of operation for the following year [1]. Nevertheless, the on-going smart agriculture utilized several data producing sensor and devices that leads to decision making and data driven process. The smart agriculture mostly developed for the remote sensing idea, which is possible by extracting the relevant data from the sensor fixed in the agriculture field [2]. Through the remotely sensing data the formers can predicted the crop yield for the upcoming years that helpful to make correct decision and avoid the loss of agricultural production [3].

Accurate yield estimations contribute both in minimizing starvation but also educating farmers' economical and decision-making processes. The crop yield prediction is essential to addressing current problems regarding food security by consideration of possible ongoing global climate change [4]. The evolution of affordable crop yields in Norway is based on various factors such as the agroclimatic conditions, soil quality, rainfall persistence, and other improved infrastructure. Increasing greater populations on the planet has caused it hard for farmers to produce food in larger quantities and of higher quality [5]. Crop yield prediction improves total agricultural productivity by educating farmers, policymakers, and stakeholders to make well-informed decisions and manage resources effectively [6]. Integrating ML, weather patterns, satellite images and historical data becomes essential for creating accurate models which encourage efficient and economically feasible farming methods [7]. The development of ML algorithms gained considerable amount attention when used with multispectral satellite imagery to forecast agricultural productivity [8]. ML techniques such as Support Vector Machine (SVM), Restricted Boltzmann Machine (RBM), Decision Trees (DT) and Artificial Neural Network (ANN) [9] are

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provide the correct prediction about the crop yield [10, 11]. However, the ML model plays an effective role in crop yield prediction the DL techniques has proven to more suitable for data mining platform, which more applicable to agricultural remote sensing studies and other applications [12]. The DL algorithms are more complicated than the basic regression models used in ML. The DL techniques are the sub-branch of the ML, which transform the original data on top of that it find the essential information from the hidden features retained dataset by applying the several layers in the DL model. The Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) are some DL techniques utilized for the crop yield prediction [13, 14]. DL models can achieve superior crop yield prediction capacities by including additional hidden layers [11]. The primary objective of the paper is to investigate the incorporating sophisticated neural network architectures by utilizing large datasets that include historical yield data, soil properties, and climate-related variables.

1.1. Motivation and Problem Statement. The increasing number of world population required to improve the agriculture production because of fulfil the food needs. So that effective crop yield perdition is required for prevent the famine. In recent year, several authors try to accurately predicting the crop yield using the DL and ML techniques through the weather and soil data. But due to the limitation of the existing techniques the effective crop yield prediction model is not attained. The existing techniques less accurate prediction with high error rate because of less effective features are utilized for the prediction model as well as raw data contained noises are not effectively removed from the dataset. The vanishing gradient issues are occurred and high training time is consumed by the existing model utilized in the crop yield prediction. Prediction model hyperparameters are not tuned in the existing work that leads to increase error prediction and provide unstable output. On motivating these issues the proposed methodology is introduced to attain the error free effective crop yield prediction.

The major contribution of the proposed method is described in the article.

* To utilize the big data for crop yield prediction, the soil, weather and other resources data's are collected from the different agriculture field and data's are stored in the Hadoop platform.
* To pre-process the data, Missing value imputation and z-score based data normalization is utilized that normalized the data as well as fill the missing value.
* To select the optimal features, Integrated Correlation Random recursive elimination (InCorRe) is utilized that decrease the training time.
* To predicting the crop yield, Multi head Residual dilated convolution assisted gated unit (MResGat) is used and model hyperparameters are tuned using African vulture optimization algorithm (AVO), which optimized the losses of network model.

The research paper is organized into five different section like Section 1 contained the basic details of the crop yield prediction methods. Section 2 contained the survey of recent crop yield prediction model with its drawback. Section 3 contain the detail explanation of crop yield prediction proposed methodology. Section 4 consists of dataset description, performance metrics, result and discussion. Section 5 contained the overcall conclusion of the proposed work with future work and references.

2. Related Work. Elavarasan et al. [16] suggested the Deep Recurrent Q-Network (DRQN) model predicting the crop yield production. The model utilized the water and soil and crop parameters to attain high accurate prediction. The DRQN model comprised of Q-Learning reinforcement learning algorithm and Recurrent Neural Network to calculate the crop yield. The data elements were feed the Recurrent Neural Network's stacked layers sequentially. The output values of the Recurrent Neural Network are mapped to the Q-values via a linear layer. The threshold and a number of parametric features were utilized to predict crop yield by the reinforcement learning agent. The DRQN model attained 17% of MAPE and 0.19% of MAE value. The training process efficiency was less in the DRQN crop yield prediction.

Khaki et al. [17] developed Deep Neural Network (DNN) for estimating the crop yield production. The DNN model effectively learn the environmental data, genes and historical data's complex and nonlinear relationship to attain accurate crop yield prediction. The model's performance has been demonstrated as slightly dependent on the precision of the weather forecast that indicated the significance of weather prediction methods. The DNN model attained 24.40% and 23.14% of RMSE value respectively in training and testing. The limitation of the model was it sometimes neglected the important features and consumes more time for crop yield prediction.

Saeed et al. [18] designed the CNN-RNN model for minimizing the challenges of crop yield prediction. The CNN-RNN model utilized environmental factors, crop genotype and management procedures and its corresponding interactions. The CNN-RNN model effectively captured the temporal dependence of the environmental element and it outperform in crop yield prediction with high accuracy. The weather and soil condition were accurately analyzed by the backpropagation that helpful to attain high performance in crop yield prediction. The CNN-RNN attained 9% and 8% of RMSE value respectively in corn and soybean yield prediction. High RMSE value was attained during the validation of the CNN-RNN model such as 24.5%.

Bhojani et al. [19] suggested the updated random weights, bias settings and an updated multilayer perceptron (MLP) neural network with a new activation function for crop production estimation by utilizing various weather parameter datasets. In order to enhance neural network performance and precise yield prediction, the model was evaluates the outcomes of several activation functions. The Updated MLP suggests three new straightforward activation functions including DharaSig, DharaSigm, and SHBSig. The suggested three model was outperformed to default sigmoid activation function. The model attained 13.46% of error in prediction and the estimation provided less effective result because of noisy dataset.

Dhivya et al. [20] developed the hybrid DL model for crop yield prediction. The hybrid model comprised of deep belief network and fuzzy neural networks system (DBN-FNN). The probability and statistic combined neural network such as DBN outperformed in the nonlinear system. The gradient diffusion issues were solved using the FNN model. The DBN-FNN model first used a productive DBN pre-training method for improved feature vector creation and model building. The prediction process was done by the FNN model and the DBN-FNN model attained 0.19% of MAE in training and 0.15% of MAE in testing. The hyperparameter were leads to not stable and less accurate prediction.

Vignesh et al. [21] suggested the Discrete Deep belief network with Visual Geometry Group (VGG) Network (DD-VGGNet) to predict the crop yield prediction. The model initially pre-processed using the Z-score normalization. Then features were extracted through the independent shearlet approach (ISA) technique. Tweak Chick Swarm Optimization technique was utilized to optimal feature selection. Finally the model used the DL DD-VGGNet for predicting the crop yield. The model evaluated by the Agriculture crop dataset that contained the 13,457 instances. The DD-VGGNet model attained 0.10 of MSE value in crop yield prediction. The DD-VGGNet model consumed more training time because of its network structure depth.

Thimmegowda et al. [22] designed the Simple multiple linear regression (SMLR) and artificial neural network models (ANN) for crop yield prediction. Weather datasets and Rice yield data from 1980-2021 were collected from the 11 districts in Karnataka. The ANN model accurately predicted the crop yield compared to the SMLR model. ANN model produced 4.1% deviated from the actual crop yield prediction. The MAE value attained among the 1.22 and 187.72 range. ANN model decreased the performance of prediction model because of its less effective training process.

Bhattacharyya et al. [23] suggested the sugarcane yield production by monitoring the soil moisture using the ensemble classifiers. The CNN, SVM and Gaussian probabilistic method (GPM) are integrated for predicting the crop yield. The ensemble technique attained high performance compared to traditional CNN model. The results of the ensemble model should helped farmers and agricultural authorities to increase productivity. Krishna River Plateau Dataset and Godavari River Plateau Dataset were used to evaluated the proposed classifies. The ensemble model attained 2.21% of MAE and 3.5% of RMSE value in sugarcane yield prediction. Ensemble model hard to lean and leads lower prediction accuracy.

Son et al. [24] developed the ML based Random Forest algorithm for early forecasting the rice crop yield by the analysis of remote sensing data. Initially, the data is pre-processed using the empirical mode decomposition (EMD) that normalized and smoothened the Normalized Difference Vegetation Index (NDVI) data from 2000 to 2018. Finally the random forest algorithm was employed to predict the crop yield. The ML model was evaluated using different performance metrics such as mean absolute percentage error (MAPE), root mean square percentage error (RMSPE), and Willmott's index of agreement (d) values. The model attained 9.3% of MAPE, 11.8% of RMSPE and 0.81d-value. Limitation of the model was it produced high error rate.

Abbaszadeh et al. [25] suggested the DL framework for accurate crop yield prediction. The framework contained the Bayesian Model Averaging (BMA) and group of Copula functions (COP-BMA) that combined the several deep neural network outputs such as 3DCNN, ConvLSTM. The framework was utilized to soybean crop

Table 2.1: Crop yield prediction models analysis

Author name & Reference	Methods	Dataset	Performance	Limitation
Elavarasan et al. [16]	DRQN	Manually collected dataset contain weather, ground water and soil data.	MAPE-17% and MAE-0.19%	Efficiency of the training process is less.
Khaki et al. [17]	DNN	Syngenta released several large datasets	RMSE Training-24.40%, Testing-23.14%	Time consumptions is high and feature selection model is not effective.
Saeed et al. [18]	CNN-RNN	Corn and soybean yield details contained dataset from 1980 to 2018	RMSE % corn yield- 9% and soybean yield- 8%	RMSE value is high during validation.
Bhojani et al. [19]	Updated MLP	Agriculture dataset.	Error-13.46%	Quality of the data are less.
Dhivya et al. [20]	DBN-FNN	Manually collected dataset contain weather, ground water and soil data.	MAE Training-0.19%, Testing-0.15%	Less accurate prediction
Vignesh et al. [21]	DD-VGGNet	Agriculture crop dataset	MSE- 0.10%	Consume more training time.
Thimmegowda et al. [22]	ANN	11 districts rice yield data in Karnataka and Weather datasets	MAE - 1.22 to 187.72 range	Performance of prediction model is less.
Bhattacharyya et al. [23]	Ensemble model	Krishna River Plateau Dataset and Godavari River Plateau Dataset	MAE - 2.21%, RMSE - 3.5%	Less prediction accuracy because of ensemble model.
Son et al. [24]	Random Forest	Multi-temporal Moderate Resolution Imaging Spectroradiometer (MODIS) data in Taiwan.	MAPE-9.3%, RMSPE-11.8%	High error occur in prediction.
Abbaszadeh et al. [25]	COP-BMA	USDA (United States Department of Agriculture) National Agricultural Statistical Services (NASS) repository	R2-0.81 RMSE-6.18 MAE-0.10	Higher RMSE value because of less quality data.

yield probabilistic estimation of over a hundred countries among three different states in the United States. The framework attained 0.81 R2 value, 6.18 RMSE value and 0.10 MAE value. Higher RMSE value was attained because the data' were not involved any pre-processing process. Table 2.1 contained the analysis of crop yield prediction model.

3. Proposed Methodology. Crop yield prediction is the one of the major key resource to increase the crop production and improve the economical level. Several DL and ML methods has been introduced for accurately predicted the crop yield. But it faces many challenges so overcome those challenges, the proposed method is developed using the DL technology. The architecture of the proposed method is given in Figure3.1. Initially, the soil, weather and other sources of wheat, rice and sugarcane crop big data are collected from various form. Then the collected data is stored in the Hadoop platform for processing the data in a distributed manner. After collecting the data, the data is pre-processed using the Missing value imputation and z-score based data normalization that decrease the noises presented in the input data. Then optimal features are selected through the InCorRe. By considering the historical soil and weather data, the crop yield is estimated through the MResGat. The prediction model losses can be optimized using the AVO. By applying these steps the proposed model effectively predicted the crop yield.

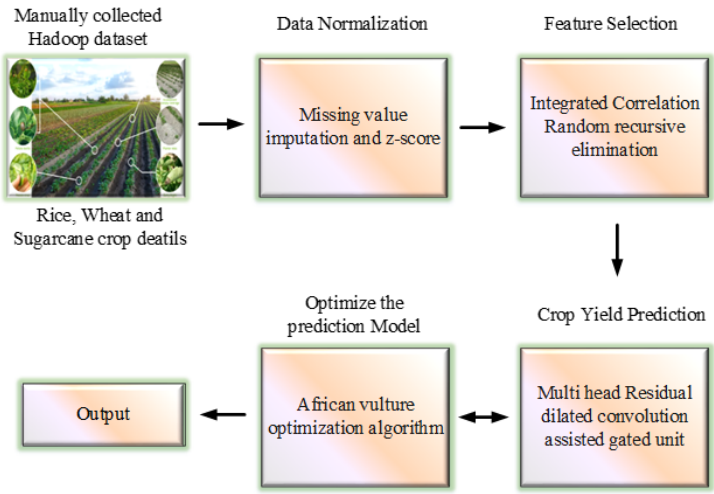


Fig. 3.1: Architecture of proposed methodology

3.1. Pre-processing using Missing value imputation and z-score based data normalization. The crop data's are rearrange and clear in the pre-processing stage, in this stage two different process can carried out such as missing value imputation moreover z-score normalization. There are a few values that are missing in the dataset, these are filled by employing the mean of all the non-missing values. The mathematical expression of the Missing value imputation has been expressed as below.

$$M_k = \frac{M_{k-1} + M_{k+1}}{2}, \quad k \in G \tag{3.1}$$

Here, M_k and M_{k-1} are represented as missing value and previous value obtained from the missing value, next value of the missing value is represented as M_{k+1} and natural number is denoted as $G = 1, 2, 3 \ldots..$ Using this process the missing values are effectively filled in the dataset. In the normalization phase, data is resized to fit within a specific range. Several normalization techniques are available here, the z-score normalization is consider for normalized the crop yield dataset. The Z-score normalization is also denoted as statistical normalization. The normalized $h^{'}$ is computed as below.

$$h^{'} = (h - \mu) / \sigma \tag{3.2}$$

Here, μ represented as set of score's mean value and σ is denoted as standard deviation. Using the z-score normalization effectively clean the data then it fed into the feature selection process.

3.2. Feature Selection Integrated correlation random recursive elimination . In this work, the InCorRe technique is utilized to find the correlation across features to select the optimal feature from the dataset. The InCorRe is selected the important features effectively that are correlated with the accurate crop yield prediction. The pre-processed data's are involved for computing correlation among the features then it checks the percentage of negative and positive correlation of features. Consequently, in order to determine the specific function of each feature, which is important to determine the correlation among all features and the target feature (status). The correlation among the features can be estimated as below.

$$Cr[f_i; f_j] = \max_{|S_i| \cdot |S_j| < B} \frac{K[S_i; S_j]}{\log_2 (\min (|S_i|, |S_j|))} \tag{3.3}$$

Here, f_i *and* f_j are the two different features in the S feature's set. The empirical parameter are defined as $B = 0.6$. The $K[S_i; S_j]$ is estimated as below.

$$K[S_i; S_j] = \sum_{S_i, S_j} p(S_i, S_j) \log_2 \frac{p(S_i, S_j)}{P(S_i)P(S_j)} \tag{3.4}$$

Here, joint probability density and marginal probability density are respectively represented as $p(S_i, S_j)$ and $p(S_i)\, and\, p(S_j)$. After calculating the correction among the features and selected the high correlated features from the pre-processed data. Then the Recursive Feature Elimination (RFE) introduced in InCorRe to eliminate the less important features. In the RFE the linear regression is selected for the recursively eliminate less important features and attained the final set of desired features. By constructing a regression line to the data, it determines the relationship between the two features. The linear regression line is expressed as below.

$$X = s * Y + t \tag{3.5}$$

Here, X and $Y$are respectively denoted as dependent features and independent features. The$s$ *and* t are denoted as slope and intercept respectively. The RFE is specify the amount of final features, based on this the RFE produced the final optimal features that increase the performance of the crop yield prediction.

3.3. Crop yield Prediction using Multi head Residual dilated convolution assisted gated unit . Four different modules are presented in the proposed crop yield prediction such as multi-head attention, time-dilated module, frequency-dilated module and prediction module. Initially the multi-head attention is employed for controlling the information mixing across different parts of an input sequence. The attention model provide the higher representation of the data and increase the performance of the prediction model. The multi-head attention makes it possible to handle numerous input sequence components in different ways that increase the performance of the prediction model. The primary elements of an attention function are a set of key-value pairs and a query, which map them to a weighted average result of all values. The input query and key with the dimension are represented as $Q_s$and K_s respectively. The attention mechanism output matrix is expressed as below.

$$Att(Q, K, V) = H\left(\frac{QK^y}{\sqrt{K_s}}\right) V \tag{3.6}$$

Here, key, value and query matrixes are denoted as K, V and Q respectively. Stacking several scaled dot-product attentions outcomes the multi-head attention. The previously mentioned queries, keys, and values can be projected linearly with time y so that various sub-space representations can be observed at different points. The projection process is attained parallel that can be display as below.

$$M\_HAtt(Q, K, V) = C\left(head_1, head_2, \ldots head_r\right) f^0 \tag{3.7}$$

Here, $head_l = Att\left(Qf_l^Q, Kf_l^K, Vf_l^V\right)$, $f_l^Q \in \Re^{s_{model} \times Q_s}$, $f_l^K \in \Re^{s_{model} \times Q_s}$,$f_l^V \in \Re^{s_{model} \times V_s}$ and $f_l^o \in \Re^{hs_V \times s_{model}}$. Attention layer and parallel head is represented as h. Compared to the single head attention, the multi head attention shows superiority and decrease the computational cost on top of that it helpful to speed up the network learning.

The network model contained 1D convolution consists of $featureMaps \times frequencyChannels \times timeSteps$ layout size's input and output layer. 1D convolution's input and output size are in $frequencyChannels \times timeSteps$ format. Each layer's hyperparameters are presented in the (kernel-Size, dilationRate, outputChannels) manner. Consider that all of the convolutions receive zero-padding. The prediction module and the time-dilated module both use batch normalization.

3.3.1. Frequency-Dilated Module. The frequency-dilated module comprises of four fixed 2D-convolution layer that gather the local spatial pattern of the input feature. The layers acquire the dilation at rates of 1, 1, 2, and 4, respectively, along the frequency direction. Subsequently, the features obtained by the frequency-dilated module require an appropriate dimensionality transformation in order to accommodate 1D convolutions in the subsequent module.

Dilated convolution is expand the contextual information of the particular fields without losing resolution. The standard convolution operator $*$ that convolves the data with the $(2n+1)\times(2n+1)$size contained kernel$h$, which is denoted as below.

$$(P*h)(k)=\sum_{r+yt=k}P(r)h(t) \tag{3.8}$$

Here, $k,r\in \mathrm{Z}^2$,$t\in[-n,n]^2\bigcap \mathrm{Z}^2$ and Z is represented as integers. An operator of the dilated version as denoted as $*_d$. The d -dilated convolution is expressed as below.

$$(P*_d h)(k)=\sum_{r+yt=k}P(r)h(t) \tag{3.9}$$

While applying kernels with rapidly increasing dilation rates, the scale of the receptive fields within dilated convolutions rises exponentially with the layer depth as opposed to the conventional convolutions. In the time-dilated convolution, one dimensional convolution r temporal convolution is employed. The dilated spatial convolution's asymmetric version is represented as the time-dilated convolution which not focus the frequency direction but the dilation focus the time direction. The dilated convolution produces a dilated spatial convolution having a kernel of size 5×5 in order to collect contextual information throughout the frequency dimension. Frequency-dilated convolutions are convolutions that participated in dilation applied to the frequency direction only, not the time direction. Nevertheless, the recent frequency-dilated convolution collect the context in both frequency and time direction.

3.3.2. Time-Dilated Module. To create the prediction model as the temporal dependencies, the several amount of residual blocks are introduced that execute the time-dilated convolution. These time-dilated modules are receive the input from the frequency-dilated module. The group of residual blocks are generate the rising edge wave to sequent increase of dilated rate. Two different following groups are repeat the similar pattern such as 1, 2, 4, 8, 16, 32; 1, 2, 4, 8, 16, 32; 1, 2, 4, 8, 16, 32. Aggregation of long-term contexts is achieved possible by residual block groups, which allow for exponential development of the receptive field while maintaining the input resolution. The prediction model utilized the type of skip connection considered in the WaveNet. Such skip connections provide all of the remainder block outputs from the time-dilated module to the next module, unlike the time-dilated module. The skip connection provide the training through the increase the data flow and enhance the gradients across the network.

The Gated Linear Unit is introduced in the work to overcome the issues of traditional gating techniques. Initially, gating strategies were intended to improve the information flow in an RNN over time. Controlling the long–term memory in the LSTM with RNN is attained through applying the forget gate and input gate. These gates avoid the issue of vanishing or exploding gradients that arises when time-propagation is used to train recurrent networks. The multiplicative unit underlying the convolutional estimation represented by LSTM gate is as follows.

$$\begin{aligned} x &= \tanh\left(z*K_1+L_1\right)\otimes S\left(z*K_2+L_2\right)\\ &= \tanh\left(u_1\right)\otimes\left(u_2\right) \end{aligned} \tag{3.10}$$

Here, $u_1=z*K_1+L_1$, $u_2=z*K_2+L_2$, biases is represented as L, kernel is denoted as K , the sigmoid function is denoted as S and the element-wise multiplication is represented as $\otimes$. Gating in the LSTM approach may allow for more complicated interactions by regulating the information flow within CNNs. LSTM-style gating gradient is given as below.

$$\nabla\left[\tanh\left(u_1\right)\otimes S\left(u_2\right)\right]=\tanh^{'}\left(u_1\right)\nabla u_1\otimes S\left(u_2\right)+S^{'}\left(u_2\right)\nabla u_2\otimes\tanh\left(u_1\right) \tag{3.11}$$

Here, $\tanh^{'}\left(u_1\right), S^{'}\left(u_2\right)\in(0,1)$, the primary sign represents differentiation. The vanishing gradient problem usually appears as the depth of the network grows and when using such gating, the downscaling factors $S^{'}\left(u_2\right)$

and $\tanh^{'}(u_1)$ make it harder to solve. To overcome these issues the Gated Linear unit is introduced that can be described as below.

$$\begin{aligned} x &= (z * K_1 + L_1) \otimes S\,(z * K_2 + L_2) \\ &= (u_1) \otimes (u_2) \end{aligned} \tag{3.12}$$

The Gated Linear unit gradient can be expressed as below.

$$\nabla\,[u_1 \otimes S\,(u_2)]\; = \nabla u_1 \otimes S\,(u_2) + S^{'}\,(u_2)\,\nabla u_2 \otimes (u_1) \tag{3.13}$$

Gradient flow is done without downscaling a path $\nabla u_1 \otimes S\,(u_2)$ using layers while keeping nonlinearity. The prediction model created a deep residual learning framework through the use of identity shortcuts, which significantly reduce the issue of the vanishing gradient. The bottleneck structure maintains performance stable while reducing the depth of the network. Through the use of exponential linear units (ELUs) and time-dilated convolutions in the common bottleneck residual block, the prediction model can enhanced the performance. The modified bottleneck residual block is improve the receptive domain by increase the middle layer kernel size. Furthermore, the proposed model change out rectified linear units (ReLUs) to ELUs for speed up learning and enhance generalization performance.

3.3.3. Prediction Module. Context of the input are combined systematically after completing the time-dilated module and frequency-dilated module. Using the combined context, the prediction module is execute the mask estimation. The prediction module contained the size 1 kernel included three convolutional layers. Among the three layers, two consecutive layers having ELUs and linear activations that were responsible to cross-channel pooling and dimension reduction respectively. The final prediction layer contained the sigmoid function and the ReLU function smooth estimation force the output of the network as positive. Figure 3.2 shows the structure of AVO-MResGat model.

AVO metaheuristic algorithm is developed depending upon the vulture hunting strategy. The AVO is employed with the prediction model to optimize the model moreover increase the performance of the crop yield prediction. To attain a best solution from the every group, the AVO initialized the population in the first stage that can be expressed as below.

$$P(l) = \begin{cases} BVo_1, & if\ M_l = n_1 \\ BVo_2, & if\ M_; = n_2 \end{cases} \tag{3.14}$$

Here, n_1 and n_2 are the pre-determined optimization parameter range among 0 and 1. If the $n_1 + n_2 = 1$, then a roulette wheel can be used to pick the optimal set resolution and to predict the probability of selecting the best option. This can be expressed as follows.

$$M_l = \frac{W_l}{\sum_{k=1}^{q} W_l} \tag{3.15}$$

Here, satisfied vultures is denoted as M, the numeric value β is 0, when α numeric value is one and vice versa. In the second step, the vulture hunger rate is computed. The vultures are currently hunting food by flying high. The vulture gathers additional groups close itself in order to obtain free food when its energy levels are low that can be given as below.

$$y = z \times \left(\sin^{\gamma}\left(\frac{\pi}{2} \times \frac{It_1}{\max_{It}}\right) + \cos\left(\frac{\pi}{2} \times \frac{It_k}{\max_{It}}\right) - 1\right) \tag{3.16}$$

$$W = (2 \times \lambda + 1) \times r \times \left(1 - \frac{It_l}{\max_{It}}\right) + y \tag{3.17}$$

Here, the random value is signified as λ that varied from 0 to 1. The present iteration is referred as It_l, the fixed number set is described as r that shows the optimization operation, which creates the operation phases and exploration phases. The total amount of iteration is referred as $\max_{It}$, a random number ranging between -2 to 2

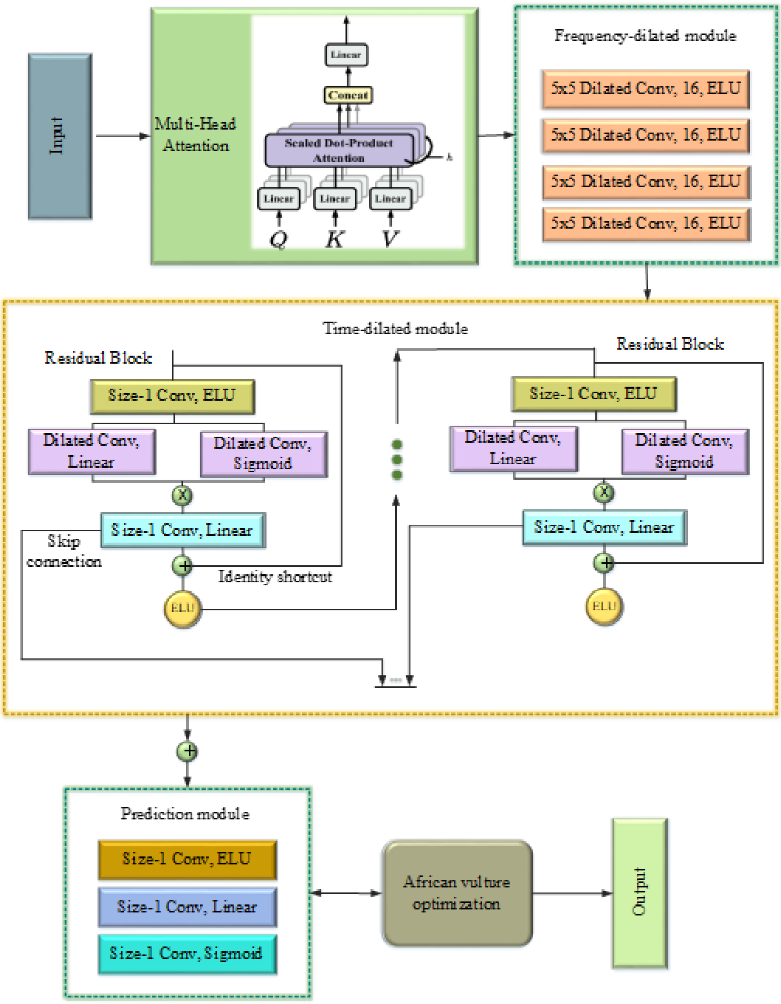


Fig. 3.2: Structure of AVO-MResGat model

is referred as x. If v reduce to zero, then the vulture is starving, or else if it rises to 1, then the vulture is satisfied.

In the third phase, vultures are random elements with two different plans and a parameter F_1 that selects the level and has a value from zero to one. Food exploration can be expressed as follows.

$$If\ \ F_1 \geq V_{F_1} :$$

$$P(l+1) = BVo(l) - S(l) \times P \tag{3.18}$$

$$If\ F_1 < V_{F_1} :$$

$$P(l+1) = BVo(l) - P + V_2 \times ((UrB - LrB)) \times V_3 + LrB \tag{3.19}$$

$$S(l) = |U \times BVo(l) - P(l)| \tag{3.20}$$

Here M referred to as the random movement of the vultures for protecting the food from other vultures, and that is established by $U = 2 \times V$, UrB and LrB are represented by the higher and minimum bound variable, respectively. The BVo consists of the best vulture, V_2 and V_3 denoted as two different random values that are limited from 0 to 1.

$$P(l+1) = S(l) \times (P + V_4) - x(l) \tag{3.21}$$

$$x(l) = BVo(l) - P(l) \tag{3.22}$$

The vultures' spiral motion can be expressed as follows.

$$a_1 = BVo(l) \times \left(\frac{V_5 \times P(l)}{2\pi} \right) \times \cos(W(l)) \tag{3.23}$$

$$a_2 = BVo(l) \times \left(\frac{V_6 \times P(l)}{2\pi} \right) \times \sin(W(l)) \tag{3.24}$$

$$P(l+1) = BVo(l) - (a_1 + a_2) \tag{3.25}$$

Aggressive conflicts and violent actions between the two sorts of food sources are occurring in order to search for food. If the $|P| < 0.5$ recognized span at the random integer (V_3) range from zero to one. If $V_{F_3} \geq F_3$, the objective was to collect various kinds of vultures around the food source. If $V_{F_3} < F_3$ the violent siege-fight is carried out. Vultures don't often go hungry, which causes intense competition among them for food that can be formulated as below.

$$D_1 = BVo_1(l) - \frac{BVo_1(l) \times P(l)}{BVo_1(l) - P(l)^2} \times P \tag{3.26}$$

$$D_2 = BVo_2(l) - \frac{BVo_2(l) \times P(l)}{BVo_2(l) - P(l)^2} \times P \tag{3.27}$$

Here, $BVo_1(l)$ and $BVo_2(l)$found the best vulture for the first and second groups. The vulture's present vector location is represented as $P(l)$, and it attained as below.

$$P(l+1) = \frac{D_1 + D_2}{2} \tag{3.28}$$

The above equation is used for calculating the vulture assembling. If $|E| < 0.5$, the healthy vultures up front lost their energy and they cannot stand on the others. Therefore, other vultures become violent because they get the food. From the main vulture, they move in several directions; it is formulated as follows.

$$P(l+1) = BVo(l) - |x(l)| \times P \times Levy(x) \tag{3.29}$$

The modification term is described as levy fight $(LevyF)$.

$$LevyF(y) = \frac{n \times \sigma}{100 \times |u|^2} \tag{3.30}$$

$$\sigma = \left(\frac{\Gamma(1+\alpha) \times \sin\left(\frac{\pi\alpha}{2}\right)}{\Gamma(1+\alpha_2) \times \alpha \times 2\left(\frac{\alpha-1}{2}\right)} \right)^{\frac{1}{\lambda}} \tag{3.31}$$

Here, n and y represented as the two different random numbers among 0 and 1, $\alpha = 1.5$set as the constant value. The overall pseudocode for the proposed method is represented in Algorithm 1.

Through the process, the proposed model effectively predicted the crop yield more accuracy and less computation time.

Algorithm 1 Pseudocode for the proposed methodology

Input : Manually collected Rice, Sugarcane and Wheat Big data stored in Hadoop platform
Begin
Pre-processing
Step1: Missing value is filled by using the equation (1)
Step2: Normalized the data within the specific range using the Z-score normalization (equation 2).
//Pre-processed data
Feature Selection using InCorRe
Step 3: Find the Correlation among the features using the equation (3)
Step 4: Selected the High correlation features for RFE.
Step 5: Choose a machine learning model (e.g., linear regression) for RFE.
Step 6: Use RFE to recursively eliminate less important features.
Step 7: Specify the desired number of final features to be retained.
//Selected optimal features
Crop Yield Prediction using AVO-MResGat
Step 8: Higher level features are selected by the Multi head attention.
Step 9: Estimate the crop yield using the MResGat Network model.
Step 14: Network model hyperparameters are tuned using the AVO algorithm.
// Prediction output
Output: Crop yield prediction
End

4. Results and Discussion. The crop yield prediction performance of the proposed model is estimated through the several performance metrics. The proposed model analyzed over the manually created dataset and the superiority of the proposed model is proven by comparing the performance with the existing model.

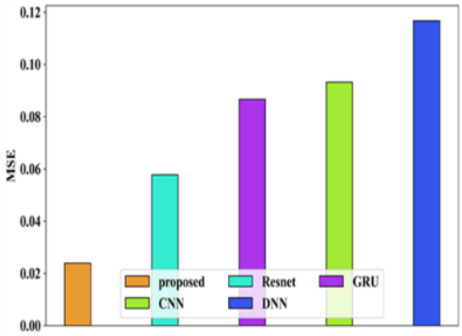
4.1. Dataset Description. The manually collected dataset comprises of Rice, Wheat and Sugarcane crop yields data's. The data's are gathered over the different years and each month of the year. The different resources of crop growth such as Rain fall, pH, temperature, humidity, Electrical Conductivity, area of the crop and farm size (hectors) also presented in the dataset. The essential nutrients are measured and updated into the dataset such as Organic Carbon (OC), Available Nitrogen (N), Phosphorus (P), Potassium (K), Sulphur (S), Zinc (Zn), Iron (Fe), Manganese (Mn), Copper (Cu) and Boron (B). Finally, the collected crop data's are stored into the Hadoop and it accessed to predicting the crop yield.

4.2. Performance Metrics . The proposed crop yield prediction model is evaluated by using the different performance metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared (R2) and Mean Absolute Percentage Error (MAPE). The performance metrics definition and corresponding mathematical expression is mentioned in this section.

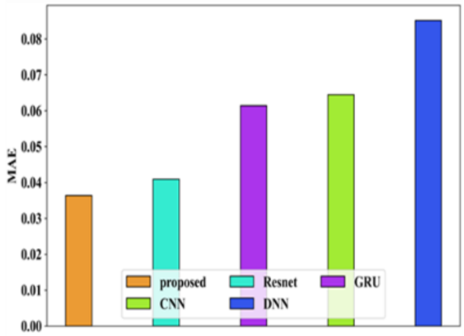
4.2.1. MSE. MSE is calculate the average squared variance among the predicted value and actual values that can be expressed as below.

$$MSE = \frac{1}{M} \sum_{k=1}^{M} (q_k - \hat{q})^2 \tag{4.1}$$

Here $\hat{q}$ and $\bar{q}$ are denoted as predicted value and mean value of $q$respectively.



(a)



(b)

Fig. 4.1: Performance analysis based on (a) MSE and (b) MAE

4.2.2. MAE. MAE is computed the average absolute changes across the predicted value and actual values that can be mathematically expressed as follow.

$$MAE = \frac{1}{M}\sum_{k=1}^{M}|q_k - \hat{q}| \tag{4.2}$$

4.2.3. RMSE. A RMSE that shows that exact far apart of the expected outcomes from the observed values through average in a dataset, the mathematical expression of RMSE is mentioned as below.

$$RMSE = \sqrt{\frac{1}{M}\sum_{k=1}^{M}(q_k - \hat{q})^2} \tag{4.3}$$

4.2.4. R2. R2 shows the percentage of the dependent variable's variance could be predicted based on the independent variable. The equation for the R-squared is mentioned as below.

$$R^2 = 1 - \frac{\sum_{j=1}^{m}(x_j - \hat{x}_j)^2}{\sum_{j=1}^{m}(x_j - \hat{x}_j)^2} \tag{4.4}$$

Here, actual value's mean is represented as$\hat{x}$.

4.2.5. MAPE. The percentage that differs between expected and actual values is measured by MAPE and mathematical equation is given as below.

$$MAPE = \frac{1}{m}\sum_{j=1}^{m}\left(\frac{|x_j - \hat{x}_j|}{|x_i|}\right) \times 100 \tag{4.5}$$

These metrics are commonly used in evaluating the performance of regression models.

4.3. Performance analysis and comparison. The performance of proposed crop yield prediction is evaluated in this section to show the superiority of the proposed model compared with the other existing system. The different performance metrics are involved to estimate the performance of crop yield prediction over the manually collected dataset. Figure 4.1 contained the performance analysis based on the MSE and MAE.

MSE estimate larger mistakes because it treated severely than smaller error. In contrast to MSE, MAE is lesser sensitive to errors. Superior model performance is demonstrated with a lower MSE that values near

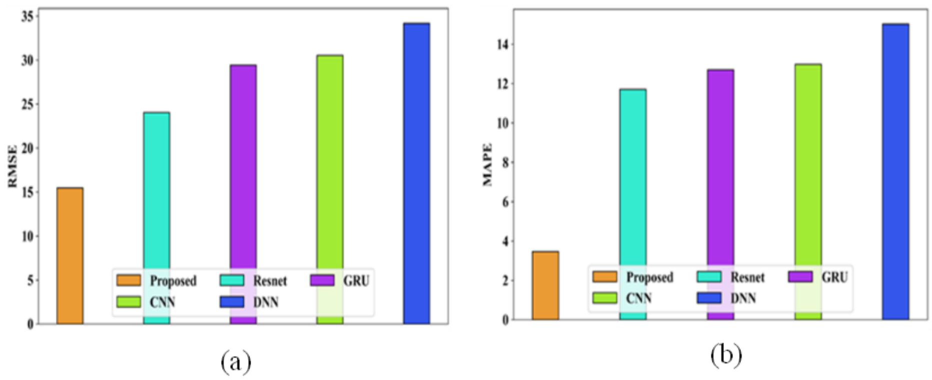


Fig. 4.2: Performance analysis based on (a) RMSE and (b) MAPE

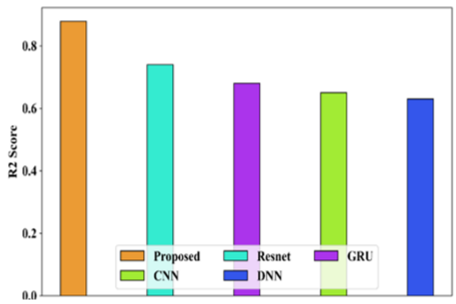


Fig. 4.3: Performance analysis based on R2 Score

to zero is most preferred. Like MSE, a lower MAE denotes better model performance because it shows the average amount of errors as well as it is simpler to understand. The proposed model attained less values in both MSE and MAE values such as 0.023 and 0.036 respectively. The proposed model has outperformed compared to other methods such as CNN, DNN, Gated recurrent units (GRU), residual network (Resnet). Figure 4.2 represented the RMSE and MAPE analysis over the crop yield prediction model.

The quality of the prediction model is measured using the RMSE value. MAPE is particularly helpful while dealing with data that has different scales, which estimate the percentage deviation among the actual and predicted values. Smaller RMSE and MAPE values are indicate the better accuracy in crop yield prediction. Based on the requirement the proposed model attained less 0.154% of RMSE value and 3.46% of MAPE value over the crop yield prediction. Figure 4.3 contained the R2 score analysis and comparison.

The R2 score estimate the goodness of the prediction fitting. The range of the R2 is set among the zero to one. A more accurate prediction is indicated by a higher R2 value, moreover the value of R2 equal to 1 shows that the model effectively predicts the dependent variable. The proposed model more effectively estimate the resources that are helpful to attain the high crop yield. The proposed model achieved 0.878 value in the R2-score that outperform compared to other prediction model. From the analysis the proposed model accurately predicting the crop yield over the manually collected dataset. Figure 4.4 consists of year wise analysis of wheat, rice and sugarcane production.

The proposed model address the time dependencies of the different crop yield such as Rice, Wheat and Sugarcane based on the number of years. From the 2018 to 2025, crop yield is predicted by the proposed model and it plotted in the above graph. Through the graph the accurate crop yield can estimated by the former. The proposed model estimation show that the wheat and sugarcane production is very high compared to the rice

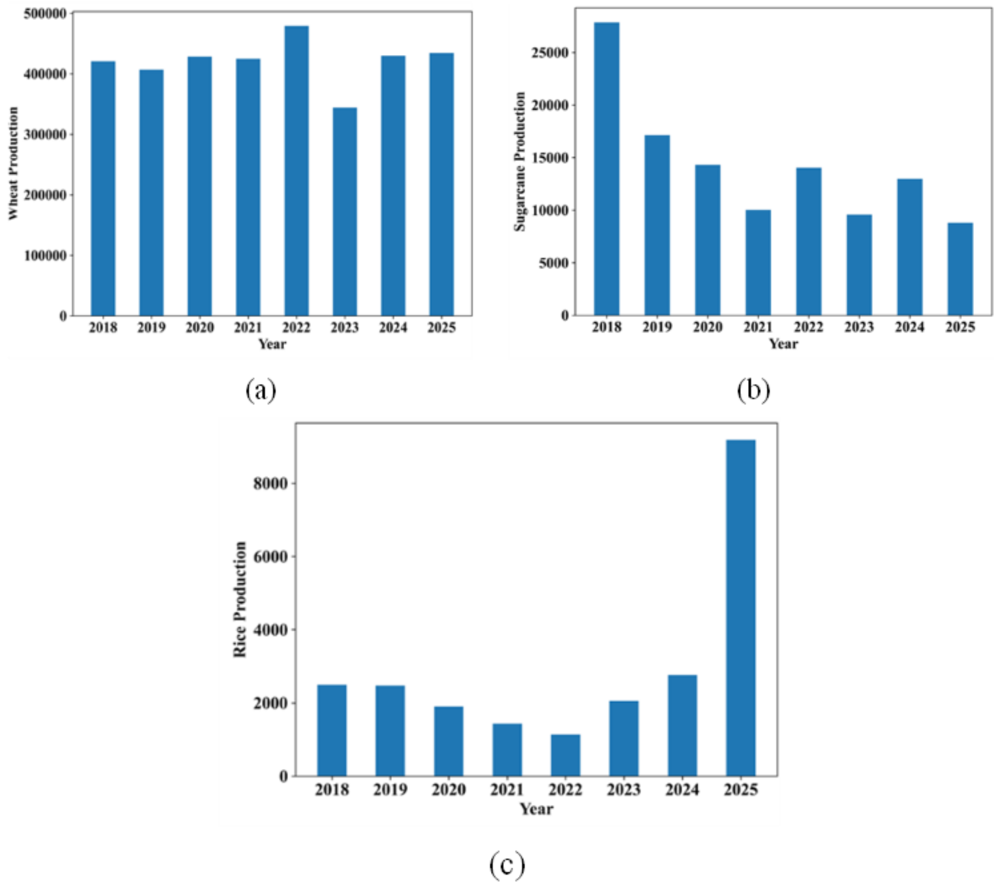


Fig. 4.4: Analysis of (a) Wheat (b) Sugarcane and (c) Rice Production at the 2018 to 2025

production. Through the analysis the former can move to cultivating more rice crop. The Wheat production is gradually increased in every year by year. At the same time the Sugarcane production is decreased in 2018 to 2021 but slightly prediction is increased in the year of 2022, like a same ratio its production is goes up and down from 2022 t0 2025. Nevertheless, the Rice production is extremely decrease from 2018 to 2022, at it gradually increased after the 2023. Figure 4.5 shows the fertilizers utilization in over the number of years.

The crop utilized fertilizers for increasing the production over the different years is analyzed in the above graph. Through the estimation the amount of fertilizers such as Phosphorus, Potassium and Nitrogen are indicated to the former for retain the crop yield. Compared to the Nitrogen and Potassium, the Phosphorus is used as lesser amount for the crop. According to the graph the maximum 991.4 nitrogen, 58.32 phosphorus and 693.332 potassium utilized for crop production. The correct amount of fertilized over the crop is essential resources for attain the high production. From the analysis, the proposed method accurately predicted crop yield by different factor presented in a collected dataset.

4.4. Discussion. Crop yield prediction plays a crucial role in agricultural planning and resource management. By leveraging data-driven models and advanced technologies, accurate predictions can be made regarding the potential harvest for a specific crop in a given region. By delving into the intricacies of DL models, this research seeks to enhance the accuracy and efficiency of crop yield predictions, thereby contributing to sustainable agricultural practices and addressing global food security challenges. Several ML and DL based crop yield prediction is developed by the various researches but it not fulfil the requirement of the accurate

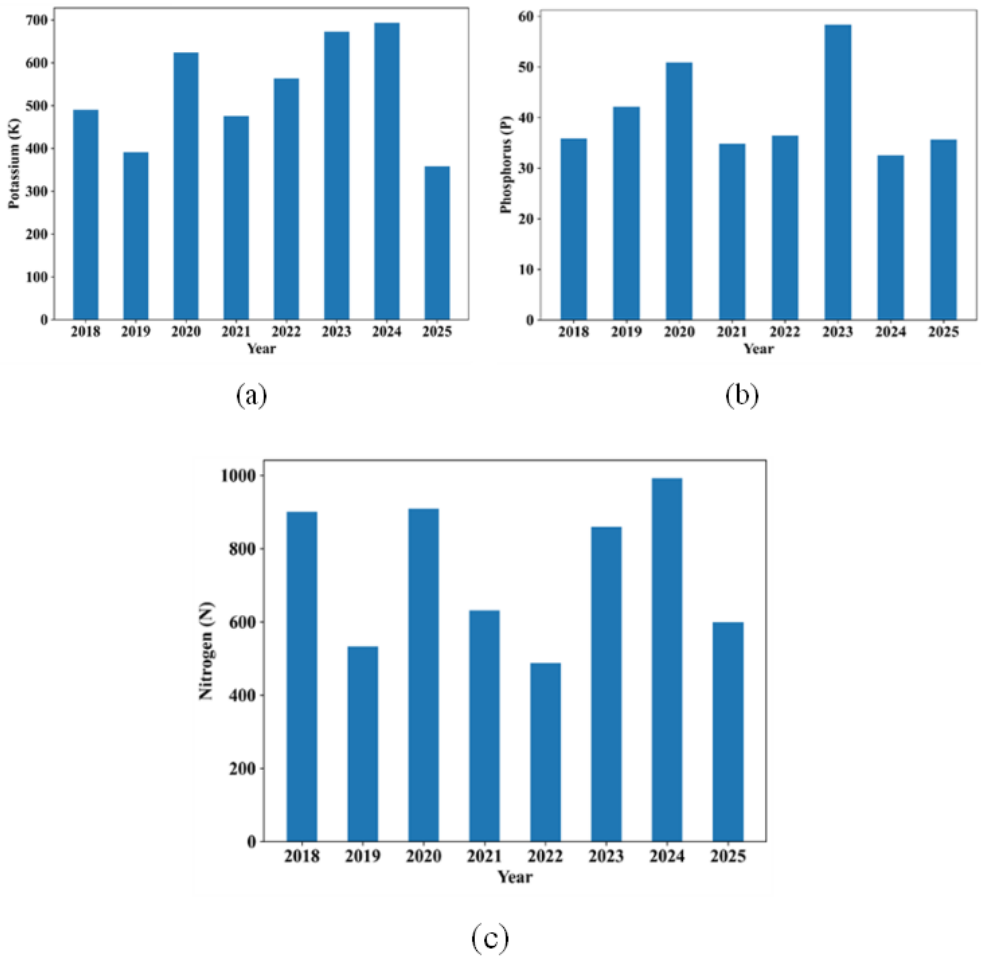


Fig. 4.5: Analysis of (a) Potassium (b) Phosphorus and (c) Nitrogen level at the 2018 to 2025

prediction. The existing crop yield prediction model not effectively done the training process which lead to less accurate prediction [16, 22]. The proposed MResGat model contained time-dilated module can perform the effective training while high data flow by the utilization of skip connection. The vanishing gradient and high computation time are another issues in the existing work [17, 21 and 23] that solved by introduce the ELU instead of ReLU which speed up the learning process and increase the crop yield prediction performance. The utilization of irrelevant features in the existing work leads to more computational time and produced high error in prediction [18 and 24]. The proposed model used the effective InCorRe approach that selected the optimal features which reduced the errors in the prediction model. The meaningless data or noisy data presented in the dataset caused the error occurrence in crop yield prediction [19, 25]. The proposed method used the Missing value imputation and z-score based data normalization pre-processing technique which fill the missing data with related data and normalized the data within the specific range. The pre-processing technique is increase the quality of the crop yield data and enhanced the prediction model performance. The some existing work given the unstable performance in prediction because of not perform the hyperparameter tuning [20]. The proposed model utilized AVO algorithm for hyperparameter tuning that decrease the prediction model losses. The proposed model attained 0.023, 0.036, 0.154, 3.46 and 0.878 values respectively in MSE, MAE, RMSE, MAPE and R20-Score. Table 4.1 contained performance comparison with the existing works.

By comparing the performance of proposed model with existing work, the proposed model prove that it

Table 4.1: Performance comparison with existing works

Author Name and References	**Model**	**MAE**	**RMSE**
Abbaszadeh et al. [25]	COP- BMA	0.10	6.18
Liu et al. [26]	Informer Model	-	0.41
Joshua et al. [27]	General Regression Neural Network	0.82	0.161
Gopal et al. [28]	MLP-ANN	0.041	-
Proposed	**AVO-MResGat**	**0.036**	**0.154**

outperform in crop yield prediction with the minimum error. Thus crop yield prediction helpful to increase the crop production in upcoming years in agriculture field.

5. Conclusion. The crop yield prediction is essential to making the correct decision about the cultivating most suitable crop belonging to the available resources. The interconnected of DL and smart agriculture is forecasting crop yield which offer shape for the future of food production. The Proposed work developed the novel DL model for crop yield prediction. Initially, the rice, sugarcane and wheat crop production details are collected from the various agriculture field and stored it into the Hadoop platform as a big data which offers the data processing in a distributed manner. The gathered raw data initially pre-processed using the Missing value imputation and z-score based data normalization that increase the quality of the dataset. After that optimal features are obtained using the InCorRe that extracted the relevant features for the prediction process. Finally the MResGat model was predicted the crop yield and its network losses can be reduced through the AVO. Utilization of complete process involved in the proposed work help to increase the performance of the crop yield prediction. The proposed work evaluated by the different performance metrics and attained high performance such as 0.023% of MSE value and 0.036% of MAE values. The proposed model outperform compared to other existing methods. The future work, focus on the increase the performance by utilizing the more effective feature selection model.

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