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# Two Level Adaptive Decision Support System For Crop Yield Prediction In Edge Cloud Enabled Smart Farming Environment Using Hybrid Deep Learning Approach

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**Abstract–**In smart agriculture, the crop yield optimization and management is highly challenging due to its adaptive environmental conditions and wide data generation. Conventional crop yield management techniques are lacked with real time data processing and precise crop yield prediction on dynamic climatic conditions with timely recommendations. To this end, we design a novel Two Level Adaptive Decision Support System (TLA-DSS) for robust crop yield management using IoT sensors and UAV in edge-cloud enabled smart farming environment. The entities involved in the proposed work such as IoT sensors, UAVs, Distributed Edge Server (DES), 6G base station, and Centralized Cloud Server (CSS). At first, the smart agricultural data from the IoT sensors and UAV are pre-processed in terms of noise reduction and Vegetation Index (VI) computation in the DES. Along with the pre-processed data and climatic data information from the weather stations are utilized for Climatic Anomaly Detection (CAD) from Multi Head Gated Recurrent Unit (MH-GRU) for examining the weather patterns. From the weather patterns, the first level recommendation are generated using Fennec Fox Optimization (F2O) algorithm. Once the first level recommendations are generated, the input values are adjusted using normalization technique. From the adjusted values, the intelligent crop yield prediction is enabled by combining Deep Learning (DL) and transformer named Adaptive Hybrid Crop Yield Prediction Network (AHPCYPN). Finally, with the same F2O algorithm, we generate second level recommendation at the cloud layer. The proposed TLA-DSS showcases the superior performance in terms of performance metrics with the existing works and algorithms by offering scalable and robust solution for modern smart agriculture.

**Index Terms –**Smart Farming, Crop Yield Prediction (CYP), Internet of Things (IoT), Unmanned Aerial Vehicles (UAV), and Deep Learning (DL)

## I. INTRODUCTION

Agriculture has remains extremely essential for the human being since it produces the majority of our food. The Food and Agriculture Organization of the United Nations states that certain portions of the world face severe food scarcity [1]. Considering the world's population expected to reach billion by 2030 and 9.6 billion by 2050 agriculture productivity must be expanded. However, climate changes and water scarcity cause's major problem in enhancing crop productivity [2]. These crop productions also affected by unpredictable rainfalls and shortage of water. In dry and desert regions water was mostly limited factor in agricultural production [3]. Therefore, a smart irrigation system is attracting more attention for its potential to support sustainable and high yielding by managing water usage. Moreover, soil types such as soil texture are very crucial as they determine capability of holding water [4], infiltration, distribution and preservation in the soil. The variation in irrigation requires water is a greatest awareness in diverse soil with different textures. Smart irrigation system automatically manages the water supplies based on the assessment and considerate water needs of soil and plants conditions. Therefore, understanding smart irrigation [5] ensure water usage can be controlled and arranged corresponding to all attainable yield target [6]. In recent decade, numerous data-driven smart irrigation systems have achieve higher development in order to determine when and how much water to irrigate with the collected data of weather, soil and plant. It is highly depending on the weather data system and uses the meteorological data to assess evapotranspiration which uses the soil water [7] balance through soil-based systems trigger irrigation while index suggesting plant water conditions exceeds predefined threshold. Despite development, this system still faces some inevitable issues therefore technologies including Internet of Things (IoT) [8], Big Data and Artificial Intelligence (AI) can be helpful to developing more effective soil-based smart irrigation methods to enhance water management and crop yield.

Smart agriculture utilizes various types of sensors to Monitor environment, crop and soil [9] conditions, generating massive amounts of data. Al and ML can interpret and evaluate this data to increase food agricultural yield. Nevertheless, the intricacy of ML algorithms makes it difficult for non-experts to grasp their judgments which might contribute to the decisions being disregarded. To be effective, ML algorithms must have a clear decision-making process. Therefore, end-users may disregard ML recommendations, rendering the algorithms worthless. Transparency [10] in AI decision-making is vital for general adoption and reliance on these systems. In ML, accessibility refers to describing models in human-friendly terms. Moreover, explainability tries to provide post-hoc solutions for balckbox models. In the case of ML, the words interpretability and explainability are equivalent. The IoT sensors are widely used for storing and managing of vast amount of data related with crop health. Several attributes are associated with plant disease such as water level and temperature [11] – [13]. The Smart sensing in agriculture are capable in analyzing which beneficial for healthy crop including what are needed, amount, time to apply resources to help farmers. It also involves collecting various data on soil nutrients, pests, weather, plant and weeds. By analyzing these collected data provides relevant recommendation for farmers. Moreover, monitoring the plants growth conditions by checking the chlorophyll helps to determine nutrients requirements. This data combined with soil characteristics and weather conditions [14] [15] helps to estimate the essential fertilizer doses. Providing farmers through real-time information ensures increase in productivity of yields.

In recent works have integrated Unmanned Aerial Vehicle (UAVs) with ML and image analysis for precision cultivation. For early-stage detection traditional methods might faces some challenges due to limited spatial resolution. Nevertheless, UAVs offer better solution by using manually defined rules based on vegetation, spectra, location and indexes for weed mapping. UAVs [16] is mostly beneficial for monitoring weed growth through practical solutions. UAV and IoT based crop yield estimation provides various advantages including real time monitoring and data collection which alerts the farmers to make decision. Additionally, high-resolution imagery and sensor data from UAVs provides accurate data on crop health [17], growth stages and potential issues. Furthermore, IoT devices can frequently collect environmental data like soil moisture and temperature to enhance the yield accuracy [18]. It also minimizes the need for human field inspections which saves both time and money [19]. Therefore, combining UAV and IoT system improve precision agriculture resulting in better resource usage and increase overall production.

To address this issue, we developed a novel Two Level Adaptive Decision Support System (TLA-DSS) for crop yield management in edge-cloud enabled [20] smart farming environment. This proposed framework involves various entities including IoT sensors and UAV, Distributed Edge Server (DSE), 6G base station and Centralized Cloud Server (CSS). At first data are collected from the IoT and UAV, then it was pre-processed through thee DES which involves noise reduction and Vegetation Indices (VI) calculation. Furthermore, the pre-processed data and the climate information from the real time weather conditions are used for Climate Anomaly Detection (CAD) by utilizing Multi Head Gated Recurrent Unit (MH-GRU). It identifies various weather patterns for taking first level immediate recommendation for instance irrigation increment during dry spells. Moreover, a Fennec Fox Optimization (F2O) algorithm is utilizing the trigger the first level recommendations. Then, based on the detected climatic conditions we adjust the input values which includes normalization and imputation. Furthermore, adjusted values are collected to perform intelligent crop yield prediction by combining Deep Learning (DL) and Transformer framework named Adaptive Hybrid Crop Yield Prediction Network (AHCYPN). Finally, based on the prediction results the second level recommendation were generated using a F2O algorithm on the cloud layer. The main contribution of our work:

1. We develop a Two Level Adaptive Decision Support System (TLA-DSS) by employing IoT sensors, UAVs and edge cloud infrastructure to allow real-time accurate crop yield management and optimization using dynamic climatic conditions.
2. Our framework uses Multi Head Gated Recurrent Unit (MH-GRU) for accurate Climatic Anomaly Detection (CAD) and Adaptive Hybrid Crop Yield Prediction Network (AHPCYPN), and combination of Deep learning and transformer method for precise crop yield predictions.
3. Our TLA-DSS method implements Fennec Fox Optimization (F2O) algorithm within edge and cloud layers to improves intelligent crop yield prediction and outperforms other existing methods in capacity and effectiveness.

## II. RELATED WORKS

In this paper authors [21] introduces a effective smart farming decisions method by utilizing a machine learning technique. This method uses the heterogeneous data environment which compresses IoT sensors data, agriculture conditions, plants features and demand. In addition, various ML and DL techniques has been utilized including Regression methods, Decision tree, Naïve Bayes, SVM, K-Means and Expectation-Maximization. Authors in [22] paper developed a Smart Agriculture which is based on IoT and Cloud to enhance crop yield production. This framework recommends appropriate seasons deployment and uses IoT cloud server for better crop yield. In addition, it suggests deep learnings methods such us Convolutional Neural-Network, Long Short-term memory and Autoencoder to improve crop yield production. Authors in the paper [23] proposed a novel crop selection framework using machine learning for smart agriculture.

It analysis the weather conditions and soil parameters using LSTM and RNN. Then the process was completed by utilizing Random Forest Classifier which provides accurate results for predicting weather. This paper authors [24] develops an AI based Smart technique for agriculture system to improve crop yield production. This method utilizes the IoT data to monitor the environment and provide warnings for farmers to take actions for maintaining perfect environments for crop production. Additionally, it uses the fuzzy logic to make the system adaptable in regard to sensors, type of crop and adaptable for all soli types and weather conditions. In this paper authors [25] presents a novel IoT security system based in artificial intelligence for better crop yield prediction. IoT collects various data such as sensors, temperature, humidity and crop health which are processed by AI to detect anomaly treats including pests, diseases and adverse weather. Authors in this paper [26] introduces a ensemble anomaly detector named ELSCP framework for smart agriculture system. This method applies two studies cases first one harvest data with combined-harvester GPS traces. Second one crop data linking crop state to anomalies which archives higher AUCPR score in combine-harvester dataset. This paper authors [27] develops a autoencoder based anomaly detection system for smart farming ecosystem. This autoencoder encodes and decodes data and identifies outliers by producing high reconstruction loss for anomalous data. Then it was trained and tested on collected data from a greenhouse test-bed and it archives higher accuracy results. In this paper authors [28] proposed a SMCSIS technique which is an IoT based multi-crop irrigation system for smart farming. This method reduces the water usage by providing real-time watering decisions which is based on soil moisture and climate predictions. In addition, it uses a five weather factors like temperature, wind, speed and direction to determine water loss. Authors in this paper [29] presents a novel IoT method based on smart agriculture automation using artificial intelligence. This method demonstrates IoT, wireless communications, ML, DL and AI can be useful in addressing challenges such crop diseases, pest control, water management and pollution in order to improve soil quality and productivity. Author in [30] introduces a intelligence agriculture crop-pest detection system by utilizing IoT automation system. This method automatically alerts the farmer mobile by detecting several pest using different types of sensors and data. The sensors are connected to a central database which collects and compare data for analysis.

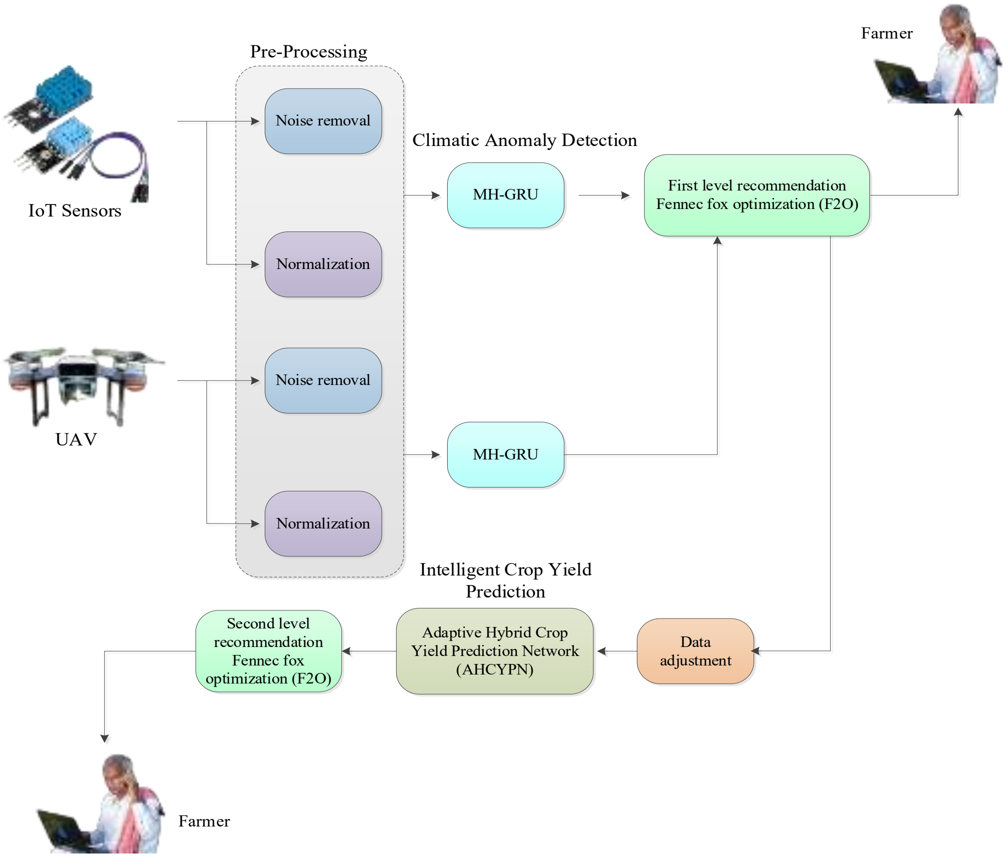
In this paper authors [31] proposed a smart irrigation system by utilizing a drip method. It incorporates both wireless sensor network and IoT cloud platform for collecting data, analytics, visualization and storage. The system makes irrigation decisions based on weather forecasts and soil sensor measurements which are updated every fifteen minutes. Authors in [32] present a low-cost smart irrigation system using a IoT and ML. This method deployed sensors like soil humidity, temperature, rain to collect data in a month by utilizing a Node-RED and MongaDB. Additionally, it was tested in various models including KNN, Logistic Regression, Neural Networks, SVM and Naïve Bayes. This paper authors [33] developed a intrusion detection by utilizing ML in IoT-Enabled Smart Irrigation. This framework uses the NSL-KDD dataset to convert the symbolic features into numeric and principal component analysis is used for feature extraction. To classify the pre-processed data, it uses several machine learning algorithms including SVM, linear regression and random forest. In this paper authors [34] presents a smart framing monitoring system using IoT and UAVs. It uses the under and aboveground sensors to gather data. This platform is helpful in predicting environmental conditions, enhancing crop productivity and farm management. Furthermore, combining IoT sensors and drones enables automated operations that enhance precision agriculture and saving natural resources. The author in this paper [35] proposed a smart agricultural industrial crop monitoring system by utilizing Unmanned Aerial Vehicle IoT classification framework.

This framework method aim is to create a crop monitoring system, at first data are pre-processed through resizing, noise removal and data cleaning. Authors in [36] paper develops a UAV-based coffee yield prediction system using feature selection and DL. This method uses UAV with RGB camera and computer vision algorithms to estimate coffee tree height and crown diameter to predict coffee yield. It collects data from 144 trees in minas Gerais and Brail, and both six parameters and LAI were used as most significant. In this paper authors [37] proposed an IoT assisted smart farming framework for crop monitoring using geospatial analysis. It evaluates the use of wireless sensors in IoT devices for application like crop status, soil preparation, pest detection and irrigation scheduling. In addition, the geographic information system is used for crop irrigation and monitoring to enhances decision-making by ensuring timely and accurate data. The authors in [38] paper introduce a crop health detection system using ML in smart agriculture system. It shares data and communicates through the help of IoT using UAV and ML which ensures high accuracy of crop disease prediction. By analysing multi-spectral image this system becomes capable of detecting the crop health through the IoT with UAV. In this paper authors [39] develops a prediction method using ML models for GS-to-UAV enabled communication. This method uses two ML algorithms such as Support Vector Regression and Artificial Neural Network to evaluate data in various scenarios through both Napier and Ruzi grass farms. Furthermore, this method is compared by utilizing statistical error indicators. Authors in [40] paper presents a rice yield detection method using UAV and DL. This method two DL method for early alert detection and yield prediction in irrigated rice. At first it uses a 3D convolutional neural network to capture spatial and temporal dimensions through multitemporal UAV images. Second uses a 2D CNN on single day images to perform error during the boosting stage through RMSEs.

## III. SYSTEM MODEL

Internet of Things sensors and UAVs (Unmanned Aerial Vehicles) are troublemaking technologies which have an extensive collision on different fields because they facilitate real-time data gathering and analysis. IoT sensors are prepared with an array of sensors to continually monitor and assemble accurate environmental data such as light, humidity, temperature, and soil moisture sensors. These sensors are necessary for applications because of their widespread deployment and wide coverage including industrial automation, smart cities, and agriculture. IoT sensors can track environmental variables, check crop health and evaluate soil conditions in precision farming to increase crop yields and resource efficiency figure1. However, UAVs also referred to as drones that are employed for data collecting and airborne monitoring. They can be fitted with multispectral sensors, high-resolution cameras, and other payloads to collect information from above and take comprehensive pictures. UAVs are very valuable in agriculture since they can make high-resolution maps, assess field conditions, and monitor crop health. Large regions may be swiftly covered by them that can increase ground-based IoT sensors with supplementary data and improving the process of gathering and analyzing data overall. Distributed Edge Servers (DES) hold and analyze data locally and near the source to provide an additional layer of efficiency. This lowers latency and bandwidth usage due to the data does not need to be transferred to a centralized server for processing. Real-time decision-making and quicker reaction times are made possible by the capacity of DES to achieve activities including data filtering, preprocessing, and localized machine learning model execution. Better scalability, bandwidth efficiency, and decreased latency are between the advantages. The functionality of 6G base stations is further enhanced by integrating these technologies with them. A 6G base station provides as the communication backbone which connects IoT sensors, UAVs and DES to the higher network that comprises the Centralized Cloud Server (CCS) by offering extremely fast connectivity, reduced latency, and increased capacity. 6G enables real-time applications and services which are necessary for time-sensitive operations due to its high data speeds, low latency, and huge connectivity. The CCS gathers information from several edge servers and conducts sophisticated data analysis, extensive machine learning model training, and long-term storage by functioning as the central hub for compute and storage. Handling large-scale data processing activities that are beyond the capability of edge servers, it combines data from a number of sources for advanced analysis and insights. Long-term trend analysis and comparisons are made easier by the capacity of CCS to accomplish sophisticated machine learning and deep learning algorithms and update locally deployed models on edge servers, and provide large-scale storage options for historical data. These technologies guarantee effective data processing, reliable data management, and prompt insight delivery when combined and propelling development in a variety of industries such as smart cities and agriculture.

**Fig 1. Illustration of Pipeline of the Proposed Method**



## A. Climate Anomaly Detection

The input is split into multiple smaller vector which allows the attention mechanism to focus on various aspects of the input in equivalent. The output attention layer is fed into the gated recurrent unit (GRU) layers which employ past timestamps to determine the networks action. Multi-head attention (MA) layer focuses on queries (Q), keys (K) and Values (V) which are vectors sequence. This vector is extracted through the same input and used to capture distinct aspects of the input data figure 2 demonstrates the MH-GRU. This MA layers analyzes multiple heads in equivalent and calculates the relevance of every head in the input. It collects the input in a form of attributes, instances and 1. Thus '1' denotes each instance. The input is separated in eight equal-size head which is calculated using (eq 1)

$$\mathrm{SI}_{\mathrm{head}} = [\frac{\mathrm{SI}_{\mathrm{Input}}}{\mathrm{M}_{\mathrm{heads}}}] \qquad (1)$$

Where $\mathrm{SI}_{\mathrm{head}}$represents the head size, $\mathrm{SI}_{\mathrm{Input}}$ represents the input sequence length and $\mathrm{M}_{\mathrm{heads}}$ denotes the total amount of heads. $\mathcal{O}, \mathcal{L}, \mathcal{U}$ values for every attention head were calculated using (eq 2, eq 3, eq 4) accordingly.

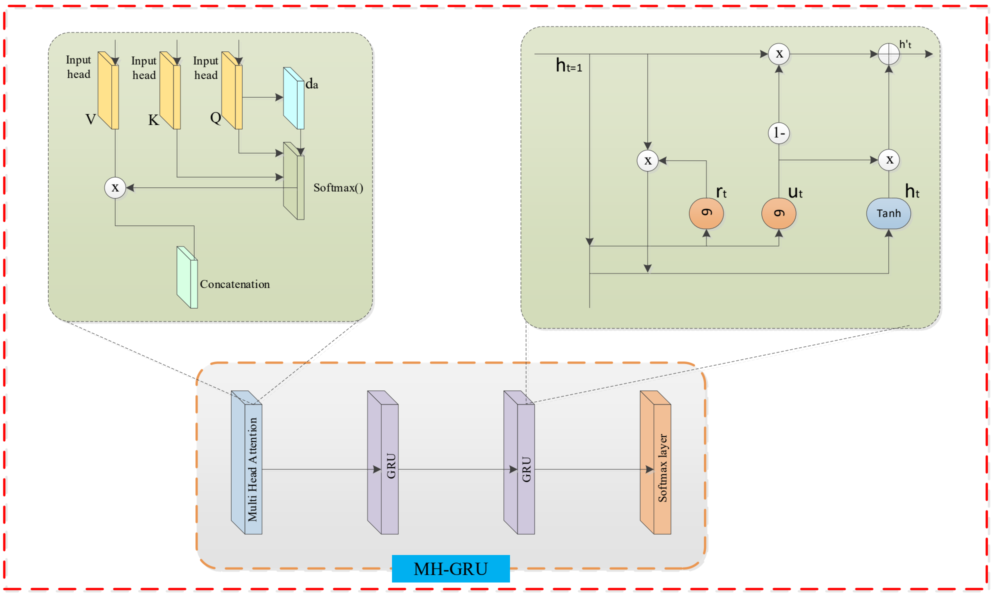
$$\mathcal{O} = \mathrm{We}_{\mathcal{O}} \times \mathrm{I} \qquad (2)$$

$$\mathcal{L} = \mathrm{We}_{\mathcal{L}} \times \mathrm{I} \qquad (3)$$

$$\mathcal{U} = \mathrm{We}_{\mathcal{U}} \times \mathrm{I} \qquad (4)$$

Here, I represents as input head, $\mathrm{We}_{\mathcal{O}}$,$\mathrm{We}_{\mathcal{L}}$, and$\mathrm{We}_{\mathcal{U}}$ denotes the learned weights. (Eq 5) is applied to calculate the attention for each head. Where $\mathrm{e}_{\mathrm{r}}$ denotes the length of $\mathcal{O}$ and $\mathrm{At}_{\mathrm{h}}$ is each attention head. At late, combine all attention heads to create the output of this layer.

Fig 2. Illustration of Multi Head Gated Recurrent Unit (MH-GRU)



$$\mathrm{At_h} = \mathrm{softmax}\left(\frac{\mathcal{O}\times\mathcal{L}^{\mathrm{T}}}{\sqrt{\mathrm{e_r}}}\right) \times \mathcal{U} \qquad (5)$$

Then, MA layer output is fed to the GRU layers. It consists of two gates; the reset gate and the update gate were associated by a single hidden state. In the GRU every gate is equipped with a sigmoid activation function while a separate tan function is utilized to generate the output as denoted. Eq 6 and 7 provide a mathematical illustration of reset and updated gates of GRU, accordingly.

$$s_u = \epsilon\left(\left(V_{xr}Y_u + V_{ir}I_{u-1} + bi_r\right)\right) \qquad (6)$$

$$t_u = \epsilon\left(\left(V_{xt}V_u + V_{tr}I_{u-1} + bi_u\right)\right) \qquad (7)$$

Here 'ru' denotes as the reset gate for a time stamp 'u' and 'iu' represents as the update gate. The previous hidden state represents as hit-1 of the GRU. The weight value denotes as 'we' and bi represents as the biases of reset and update gates. The value of the hidden state is demonstrated using (ep 8 and ep 9).

$$\widetilde{hi}_t = tanh\ \left(we_{ix}Y_u +\ we_i I(r_u I_{u-1}) + bi_u)\right) \qquad (8)$$

$$h_t = (1 - t_u)I_{u-1} + t_u\widetilde{hi}_t \qquad (9)$$

## B. First Level Recommendation Generation

Once the climatic anomalies are predicted, we generate first level crop yield recommendation using Fennec Fox Optimization (F2O) algorithm. The adopted F2O tends to optimize the convinced key variables for enhancing the real time crop yield from data inputs. More clearly, the F2O is inspired from the fennec fox hunting behavior which is used to find out the optimal solution in the search space. The objective function F2O based first level recommendation is provided as below,

$$f(y) = \sum_{j=1}^{m} we_j . Vg_j(y) \qquad (10)$$

From the above equation, $f(y)$ is the decision variables which includes fertilizer amounts, level of irrigation etc..,. The vegetation index is defined by $Vg_j(y)$, and $we_j$ denotes the weights assigned to every crop based on their priority.

At first the population of fennec foxes are initialized randomly $Y = \{y_1, y_2, \dots, y_m\}$ on the search space. Also initialize the algorithm specific parameters (i.e., fox movements coefficients, and learning rates), and number of iterations $(T)$. After that we compute the fitness of every fox using objective function $f(y)$. The fitness function can be formulated as,

$$f(y) = \sum_{j=1}^{m} we_j . X_j(y) - \beth . Co(y) - \varphi . Ri(y) \quad (11)$$

From the above equation, the crop yield which is predicted can be denoted as $X_j(y)$, the cost function is denoted as $Co(y)$ that represents the resource usage (i.e., fertilizer, water, etc..) and $\beth$ is the resource usage penalty factor. $Ri(y)$ is the risk factors from the climatic anomalies using MH-GRU and $\varphi$ is the risk penalty factor. The factors that are consider for examining the fitness values such as historical crop yield data, resource constraints, soli conditions, climatic conditions, and vegetation indices.

Once the fitness function is computed, the movements and positions of the fox are updated entrenched on its hunting strategy and can be formulated as,

$$y_j^{(t+1)} = y_j^{(t)} + \rho . \left(y_{best}^{(t)} - y_j^{(t)}\right) + \tau . \exists \quad (12)$$

Where$y_j^{(t)}$ defines the j-th fox position at the t-th iteration, the best position of the fox in current population is determined by $y_{best}^{(t)}$, the movement dynamic controlling co-efficient can be denoted by $\rho$ and $\tau$ respectively, and exploration vector can be denoted by $\exists$. When the positions are updated, we ensure that the $y_j^{(t+1)}$ is in search space bound. At last, the best solution is updated. Finally, the formulation of first level recommendation for a specific variable is provided as below,

$$Fer_{recc} = y_{opt}[Fer] \quad (13)$$

Where, $Fer_{recc}$ denotes the specific recommendation variable (i.e., recommended fertilizer), and $y_{opt}$ denotes the optimal decision variables. Based on the optimal set of decision variables, we adjust the detected climatic conditions using normalization technique. The formulation of normalization is provided in terms of rainfall, humidity, and temperature respectively. We utilize min-max normalization technique to normalize the climatic variables which are provided as below,

$$Te_{Norm} = \frac{Te - Te_{mini}}{Te_{maxi} - Te_{mini}} \quad (14)$$

$$Hu_{Norm} = \frac{Hu - Hu_{mini}}{Hu_{maxi} - Hu_{mini}} \quad (15)$$

$$Ra_{Norm} = \frac{Ra - Ra_{mini}}{Ra_{maxi} - Ra_{mini}} \quad (16)$$

From the above equation, $Te_{Norm}$, $Hu_{Norm}$, and $Ra_{Norm}$ denotes the normalized temperature, humidity, and rainfall values respectively that are provided as an input. On the whole, the normalized fitness value can be formulated as,

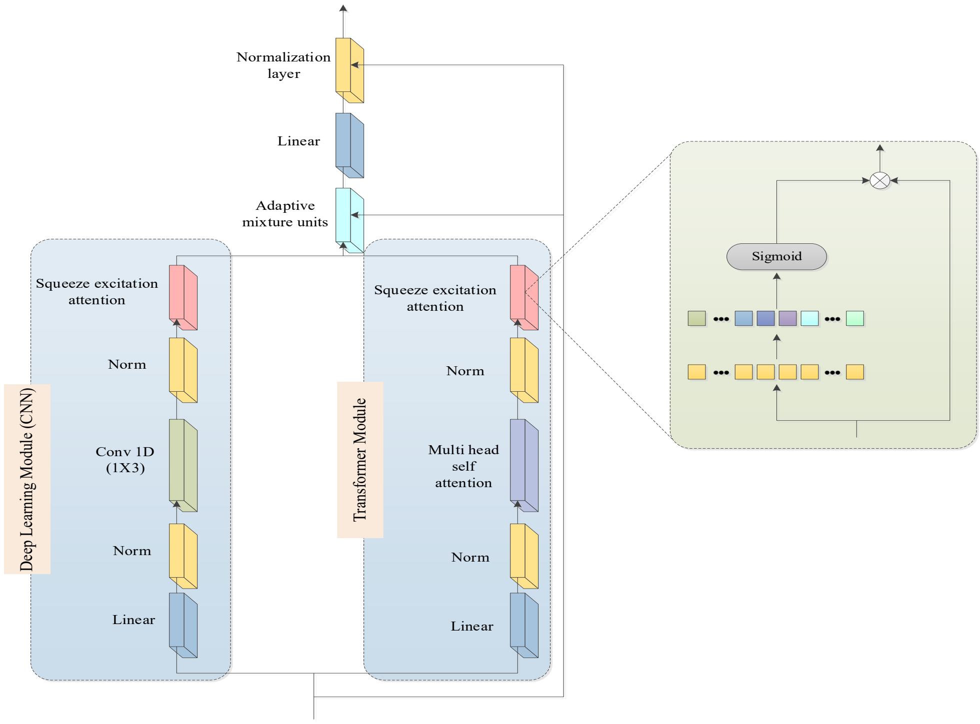
$$f(y, Cl_{Norm}) = \sum_{j=1}^{m} we_j . (\beta_j . Vg_j(y, Cl_{Norm}) + \alpha_j) - \beth . \sum_{i=1}^{n} Co_j . y_j - \varphi . MAGRU\ (Cl_{Norm}) \quad (17)$$

From the above equation, $Cl_{Norm}$ denotes the normalized climatic variables, $Vg_j(y, Cl_{Norm}) + \alpha_j$ denotes the climatic variables influenced vegetation index of the j-th crop.

## C. Intelligent Crop Yield Prediction

The adjusted climatic inputs values along with the crop yield data are provided as an input to the Adaptive Hybrid Crop Yield Prediction Network (AHCYPN) which composed of three modules such as squeezed attention transformer module (i.e., global attention), squeezed attention convolutional module (i.e., convolution neural network), and Dynamic Mixture Module (DMM) figure 3 demonstrate the AHCYPN. The module details are shown as below,

**Fig 3. Illustration of Adaptive Hybrid Crop Yield Prediction Network (AHCYPN)**



(i) Transformer Module: The transformer layer initially composed of linear layer followed for normalization layer for effectively adjusting the dimensionality in latent space for amplifying the non-linear representation. After that, the Multi Head Self Attention (MHSA) and normalization layer are involved for examining the global and contextual dependencies. At last Squeeze and Excitation Layer (SEL) is presented for assigning the feature importance level by re-weighting mechanism. The mathematical formulation involved in the transformer modules are provided as below,

$$Tra_{Glo}^{l} = SEL(MHSA(\mathcal{E}_{en}^{glo}(\forall_{(v)}^{l-1}) \otimes MHSA(\mathcal{E}_{en}^{glo}(\forall_{(v)}^{l-1}))) \quad (18)$$

$$MHSA(\left(\mathcal{E}_{en}^{glo}(\forall_{(v)}^{l-1})\right) = LaN(DRP(Con(he_1, \dots, he_k)U^{o})) \quad (19)$$

$$he_l = Att(\mathcal{E}_{en}^{glo}(\forall_{(v)}^{l-1})U_l^{qu}, \mathcal{E}_{en}^{glo}(\forall_{(v)}^{l-1})U_l^{Ke}, \mathcal{E}_{en}^{glo}(\forall_{(v)}^{l-1})U_l^{Va}) \quad (20)$$

$$Att(Qu, Ke.Va) = Smax(\frac{QuKe^{T}}{\sqrt{d_{mod}/E}} + att_{mask})Va \qquad (21)$$

$$\mathcal{E}_{en}^{glo}(\forall_{(v)}^{l-1}) = LaN\left(DRP\left(Lin_{en}(\forall_{(v)}^{l-1})\right)\right), \forall_{(v)}^{o} = \mathcal{E}(S_{1:m}^{(v)}) \quad (22)$$

$$att_{mask} = [b_{ji}] = \begin{cases} b_{ji} = 0, & Else \\ b_{ji} = -\infty, & For\ j < i \end{cases} \qquad (23)$$

From the above equations, $Tra_{Glo}^{l}$ denotes the l-th transformer module output, $SEL()$ denotes the sequence level processing using squeeze and excitation module, the element level multiplication is denoted by ⨂, the output of AHCYPN is denoted as $\forall_{(v)}^{l-1}$ in the l-1th layer. Furthermore, the $LaN, and\ DRP$ are the normalization layer and dropout mechanisms respectively. The attention layers are denoted by $E$ with attention head parameters such as $U_l^{qu}$,$U_l^{Ke}$, and $U_l^{Va} \in R^{d_{mod} \times d_{mod}/E}$respectively. Finally, the $att_{mask}$ denotes the attention mask which is firmly set to $-\infty$ or 0 to resolve the overly problems.

(ii) Convolution Module: The initial operations are similar to the transformer module which also includes linear layer and normalization layers respectively. The formulation is provided as below,

$$\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right) = LaN\left(DRP\left(Lin_{en}\left(\forall_{(v)}^{l-1}\right)\right)\right), \forall_{(v)}^{0} = \mathcal{E}(S_{1:m}^{(v)}) \quad (24)$$

Different from the previous module, the transformer module is replaced by convolutional layer of kernel size 4 and also followed by normalization layer on $\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right) \in R^{n\times d_{mod}}$. Let us say, we have adopted n-1D convolutional filters $fil^{j} \in R^{k\times d_{mod}}, j \in \{1,2,\dots,n\}$ of ker kernel size. The $fil^{j}$ gets interrelated with each of the $\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right)$ by maintaining zero padding and convolutional layer dimension. Once sliding on every position, the 1D CNN layer output can be formulated as below,

$$Con_{mid}^{Ker=3}(\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right) = LaN(DRP([Con_{mid}^{Ker=3}(\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right)))_{1}, \quad (25)$$

$$\dots, Con_{mid}^{Ker=3}(\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right)_{i}, \dots, Con_{mid}^{Ker=3}(\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right)_{m} \quad (26)$$

$$Con_{mid}^{Ker=3}(\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right)_{i} = Con(C_{i}^{1}, \dots, C_{i}^{n}) \in R^{n} \quad (27)$$

$$C_{i}^{1} = \propto (\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right))[i: i+k-1]^{fil^{j}} \quad (28)$$

From the above equation, $\propto (.)$ convolution layers activation function. The supplementary sequence values is denoted by $\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right))[i: i+k-1]^{fil^{j}} \in R^{k\times d_{mod}}$ from $i\ to\ i+K-1$. The $Con_{mid}^{Ker=3}(\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right)_{i} \in R^{n}$ denotes the position of convolution in i-th position. In addition to that, the output of the convolution module is provided to the SEL layers for sequence level re-weighting. The formulation is provided as below,

$$L_{Con} = SEL(Con_{mid}^{Ker=3}(\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right)) \otimes Con_{mid}^{Ker=3}(\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right) \quad (29)$$

(iii) Dynamic Mixture Module (DMM): The DMM is designed to ensure trade-off among the convolution and transformer module respectively. To be clearer, the dimension entrenched statistics are generated by adopting average pooling layer and $\Phi$ activation function is utilized for examining dynamic co-efficient on every input and can be formulated as,

$$Dyn^{(v)}\left(\forall_{(v)}^{l-1}\right) = \Phi(Lin_{mid}(pool(\forall_{(v)}^{l-1}))) \quad (30)$$

$$Pool\left(out\left(\forall_{(v)}^{l-1}\right)\right) = \frac{1}{m}\sum_{j=1}^{m} out\left(\forall_{(v)}^{l-1}\right)_{j} \quad (31)$$

From the above equation, the data preference at the l-1th layer can be denoted as $Pool\left(out\left(\forall_{(v)}^{l-1}\right)\right)$, the scaling function used in this work is $\Phi(.)$ sigmoid activation function. The output of l-1th layer is denoted as $\forall_{(v)}^{l-1}$. $Dyn^{(v)}\left(\forall_{(v)}^{l-1}\right)$ denotes the personalized dynamic co-efficient operation based on the varied climatic data. At last, this research mix the $Tra_{Glo}^{l}$ and $\mathcal{E}_{en}^{loc}\left(\forall_{(v)}^{l-1}\right)$ using $Dyn^{(v)}$ for representing global-local-contextual dependencies as,

$$DM_{Con}^{Tra} = Dyn^{(v)}\left(\forall_{(v)}^{l-1}\right) \otimes L_{Con} + (1 - Dyn^{(v)}\left(\forall_{(v)}^{l-1}\right)) \otimes \qquad Tra_{Glo}^{l}$$

(33)From the above equation, $Dyn^{(v)}\left(\forall_{(v)}^{l-1}\right)$ and $1 - Dyn^{(v)}\left(\forall_{(v)}^{l-1}\right)$ are the dynamically mixed input data which can be linearly adjusted from residual connection in the l-1th layer as,

$$\forall_{(v)}^{l} = LaN(\forall_{(v)}^{l-1} + DRP(Lin_{out}(DM_{Con}^{Tra}))) \quad (34)$$

## IV. EXPERIMENTAL EVALUATION

This section provides the implementation results of the proposed Two Level Adaptive Decision Support System (TLA-DSS) for crop yield prediction. We perform predictions on 6 crops which includes sorghum, soyabeans, rice paddy, maize, potato, and wheat. Our propounded TLA-DSS effectively predicted the crop yield by implementing with weka tool. We utilize both the IoT sensors and UAV images for robustly predict the crop yield by designing better decision support system.

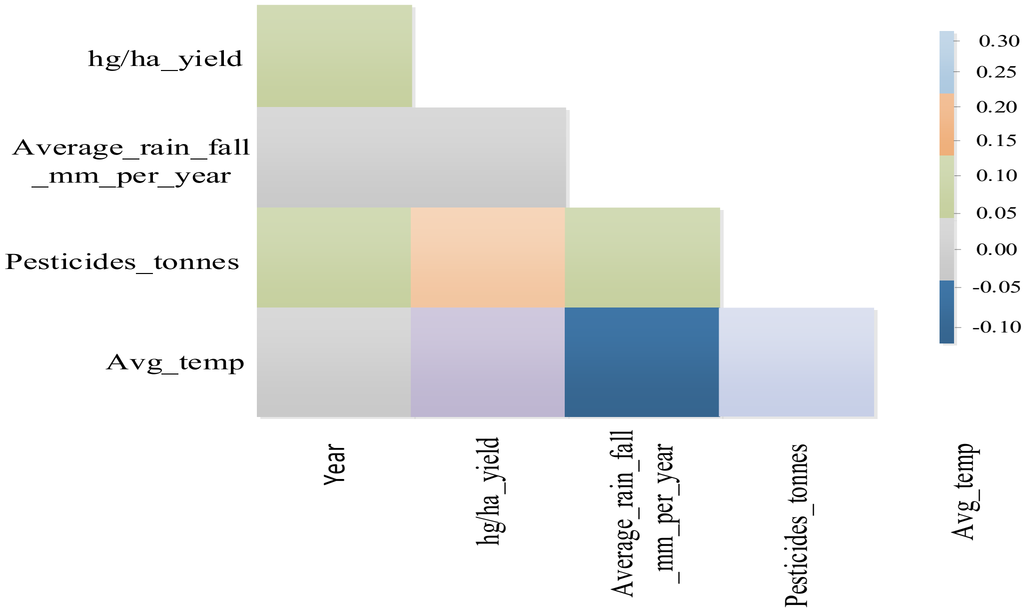
### A. Dataset Details

A Crop Yield prediction dataset is employed in this investigation. Yield and pesticides are congregated from FAO. Climate averages and rainfall are resourced from the World Data Bank. The final dataset, yield_df.csv, was making by cleaning and merging the data on pesticides, yield, rainfall, and average temperature. A sample of the implemented dataset is displayed in the table. The HeatMap for the employed dataset is shown in Figure 4.

**Table I. Representation on area heatmap**

| Area | Item | hg/ha_yield | Average_rain_fall_mm_per_year | Pesticides_tonnes | Avg_temp |
|---|---|---|---|---|---|
| Albania | Wheat | 30198 | 1485 | 121 | 16.38 |
| Albania | Potatoes | 66668 | 1485 | 121 | 16.38 |
| Albania | Maize | 36614 | 1485 | 121 | 16.38 |
| Albania | Rice, paddy | 23334 | 1485 | 121 | 16.38 |
| Albania | Soybeans | 7001 | 1485 | 121 | 16.38 |
| Albania | Sorghum | 12501 | 1485 | 121 | 16.38 |

**Fig 4. Illustration of HeatMap**



## B. Performance Assessment

The results of the implementation of the proposed work are compared in two ways such as: (i) Results of using conventional Machine Learning (ML) and Deep Learning (DL) method (ii) Results compared with existing works.

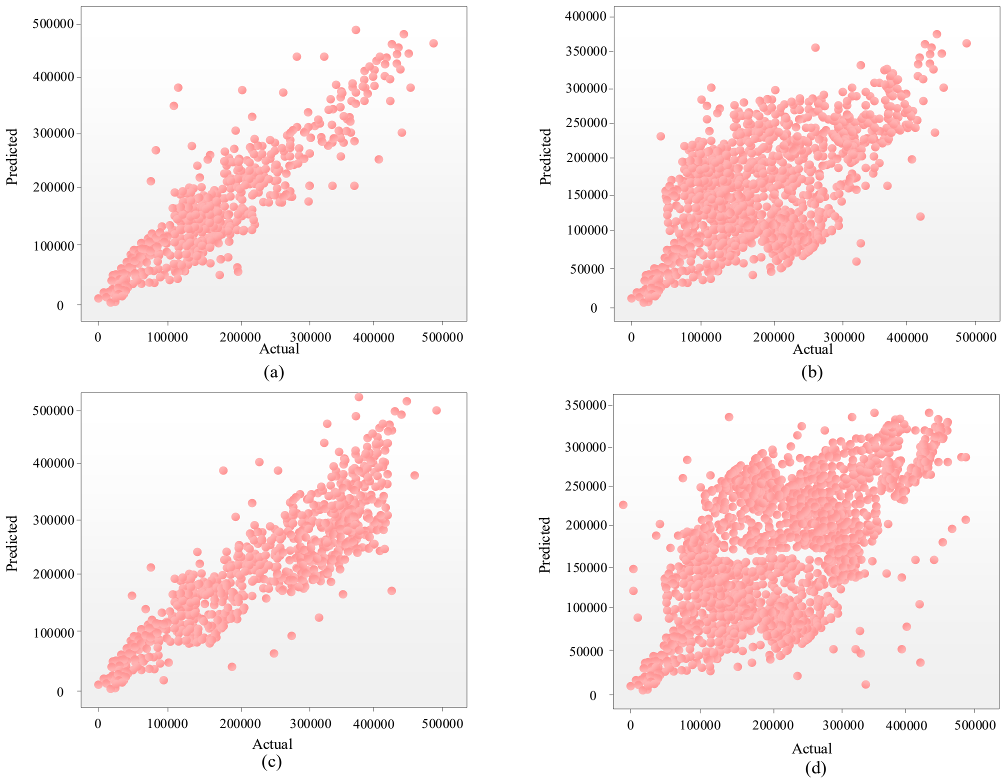
### (i) Results from Conventional ML and DL Methods

The predicted values for every crop are shown in Table by employing the algorithms and our proposed work such as SVM, CNN, RNN and TLA-DSS. Fig 5(a)-5(d) shows about the Actual data and predicted data by utilizing SVM, CNN, and RNN with the proposed work TLA-DSS. Moreover, by utilizing SVM the score was 0.9815. While we utilize CNN the score was 0.9905. And also, the RNN have scored 0.9935. At last, our proposed work TLA – DSS have scored 0.9965. Our proposed work has achieved better score in Potatoes, Sorghum, Rice, paddy, sweet potatoes, Yams, Cassava, Soybeans and Wheat while compared to SVM, CNN and RNN. Unfortunately, our proposed has attained lower score in Maize and plantations and others while compared to SVM, CNN and RNN.

**Table III. Comparison of Predicted Crop Yield on Conventional ML and DL Method vs Proposed Method**

| Crop | SVM | CNN | RNN | TLA-DSS |
|---|---|---|---|---|
| Maize | 72.1052 | 44.3500 | 34.3709 | 57.3271 |
| Potatoes | 65.7500 | 49.2102 | 69.3540 | 91.8640 |
| Sorghum | 62.2501 | 56.6723 | 46.6916 | 82.1285 |
| Wheat | 70.3025 | 62.5656 | 52.3807 | 90.2550 |
| Plantains and others | 80.1021 | 73.4534 | 53.8415 | 55.1189 |
| Rice, paddy | 72.5401 | 60.9478 | 50.4945 | 88.6403 |
| Sweet potatoes | 71.5565 | 66.8292 | 56.5816 | 81.8674 |
| Yams | 73.6067 | 61.7121 | 71.8454 | 93.7968 |
| Cassava | 75.5013 | 63.3033 | 73.5649 | 94.8895 |
| Soybeans | 87.2710 | 65.3565 | 36.0522 | 95.8468 |

**Fig 5(a) Crop Yield Prediction on SVM, (5b) CNN, (5c) RNN and (5d) TLA-DSS**



(a) (b)

(c) (d)

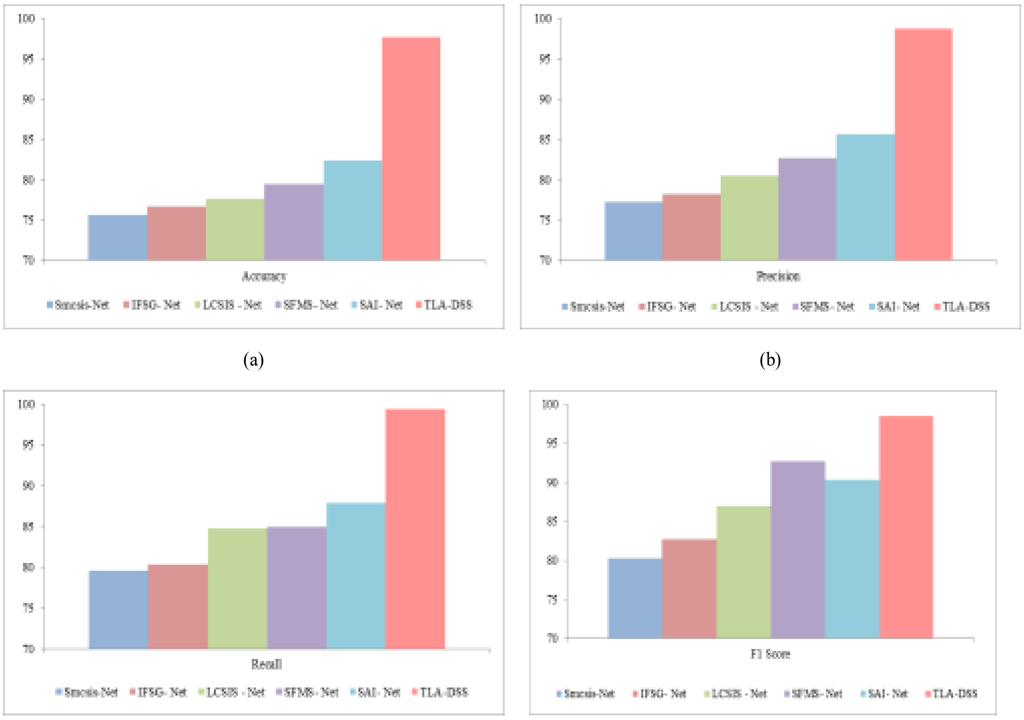
### (ii) Results from Existing Works

In this section, we have compared our proposed work TLA-DSS with other existing works such as Smcsis-Net, IFSG- Net, LCSIS – Net, SFMS- Net and SAI- Net. And also, we have compared the performance by utilizing the various performance metrics such as Accuracy, precision, Recall and F1 score. Fig 6a shows about the accuracy values that displays that our proposed work has achieved better performance in accuracy and achieved 97.65 while compared to other existing works. The existing works have attained 75.69, 76.69, 77.65, 79.46 and 82.34 in the performance of accuracy. In this SAI- Net has performed better than all other existing works. Fig 6b shows about the precision values for existing works and proposed work. Here also SAI-Net has attained better performance than other existing works and has scored 85.66. But our proposed has achieved 98.67 while compared to the recent model SAI-Net. Fig 6c shows about the Recall values for existing works and proposed work. Here, our proposed work has achieved 99.39 while compared to other existing works. The existing works have achieved lower score of 79.65, 80.36, 84.77, 84.98 and 87.92 in the performance of Recall. At last, we have also compared our proposed work in F1 score with other existing work that shown in fig 6d. Here SFMS- Net model have achieved high score while compared to other existing works. But our proposed attained 98.45 in F1 score than the SFMS- Net model.

**Table IV. Comparison on existing model vs proposed work**

| Existing work | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Smcsis-Net [28] | 75.69 | 77.25 | 79.65 | 80.32 |
| IFSG- Net [30] | 76.69 | 78.25 | 80.36 | 82.67 |
| LCSIS - Net [32] | 77.65 | 80.55 | 84.77 | 86.95 |
| SFMS- Net [34] | 79.46 | 82.66 | 84.98 | 92.66 |
| SAI- Net [35] | 82.34 | 85.66 | 87.92 | 90.36 |
| TLA-DSS | 97.65 | 98.67 | 99.39 | 98.45 |

**Fig 6(a). Comparison of Accuracy on Proposed vs Existing, (6b) Comparison of Precision on Proposed vs Existing, (6c) Comparison of Recall on Proposed vs Existing, (6d) Comparison of F1 Score on Proposed vs Existing**



(a) (b)

(c) (d)

## V. DISCUSSION

The proposed Two Level Adaptive Decision Support System (TLA-DSS) is suggested for crop yield management in an edge-cloud enabled smart farming setting showcases outstanding proceeds in precision agriculture with its comprehensive approach. The combination of Internet of Things (IoT) sensors, Unmanned Aerial Vehicles (UAVs), Distributed Edge Servers (DES), 6G base stations, and Centralized Cloud Servers (CCS) creates a incorporated and all-encompassing transportation which will efficiently administer assorted agricultural data streams. IoT sensors and UAVs are employed for robust data collecting and pre-processing in the early stage to guarantee high-resolution and real-time data acquisition. Pre-processing operations such as noise reduction and the computation of Vegetation Indices (VI) are managed by the DES and improving the quality of the data for presently phases of study. Crop yield prediction and anomaly detection depend on this clear and trustworthy data. The Multi-Head Gated Recurrent Unit (MH-GRU) is implemented for Climatic Anomaly Detection (CAD) and identifies changing weather patterns essential for quick agricultural choices, is a critical part of the system. Recommendations from the MH-GRU are precise and timely due to its capacity to measure many aspects of climate data concurrently and incarcerate temporal dependencies. The Fennec Fox Optimization (F2O) algorithm begins first-level recommendations that provide prompt measures including adjusting irrigation during dry periods. This enables farmers to promptly adapt to unfavorable weather conditions and minimize possible detrimental effects on crop health and productivity. Following these suggestions, the system normalizes and attributes input values related on identified meteorological conditions and conserving data integrity for ensuing studies. The flexibility of system is maximized by this dynamic response to modifies in the surroundings. The Adaptive Hybrid Crop Yield Prediction Network (AHCYPN) combines Deep Learning (DL) and transformer techniques for improved predictive performance and it is the brains behind the TLA-DSS's intelligent crop yield prediction. The precision and versatility of the AHCYPN are important for producing trustworthy forecasts which guide the actions of farmers. Second-level suggestions are offered at the cloud layer by the F2O algorithm. They offer both instant and long-term guidance based on crop production projections that improve the crop management during the growing season. TLA-DSS is better to existing systems in terms of accuracy, responsiveness, and adaptability, according to comparative studies. Real-time processing and decision-making are made probable by the system's integration of cloud and edge computing resources. The research has significant ramifications since it offers a scalable and useful reaction to contemporary agricultural issues by employing cutting-edge algorithms, 6G, IoT, and UAV technology. In order to confirm TLA-DSS's adaptability and scalability, future research could investigate deploying the technology in various geographic and meteorological settings as well as incorporating other data sources including market and soil health sensor data.

## VI. CONCLUSION

The proposed Two-Level Adaptive Decision Support System (TLA-DSS) develop a effective framework for crop yield management in edge-cloud enabled smart farming environments. This framework incorporates various advanced technologies including IoT sensors, UAVs, 6G base stations and centralized cloud servers. Our system main goals are to efficiently addresses the issues of real-time data processing, accurate yield prediction and timely decision making. In addition, this method utilizes the Multi-Head Gated Recurrent Units (MH-GRU) for Climatic Anomaly Detection and Adaptive Hybrid Crop Yield Prediction Network (AHCYPN) in order to enhance accuracy and flexibility. Furthermore, Fennec Fox Optimization (F20) algorithm which is beneficial for instant and strategic recommendations by improving the systems awareness. In the end, TLA-DSS provides an adjustable and productive solution for modern agriculture by extensively enhancing crop yield management and resource utilization.

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