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Timestamp Feature Variation based Weather Prediction Using Multi-Perception Neural Classification for Successive Crop Recommendation in Big Data Analysis

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Abstract— The recent generation has a lot of information for analysing growth in future prediction. Especially India is an extensive agricultural resource for the world's expansive economic growth. But in extensive data analysis, a problem for the recommendation of the seasonal crop is tedious because of improper feature analysis due to varying periods in weather conditions. So time variation-based big data analysis is essential for research improvement. To resolve this problem, we propose a Timestamp feature variation-based weather prediction using multi-perception neural classification (TFV-MPNC) for successive crop recommendation in big data analysis. Initially, the pre-processing was carried out to prepare the redundant noise dataset for fast prediction. Initially, the Preprocessing ensures the Contemporary Forecasting rate (CFR) for predicting the previous deficiency rate. Based on that Time stamp feature analysis (TSFA). The Dense region harvest rate (DRHR) was evaluated, and features were decision using Fuzzy intensive decision Function (FIDF), selected the scaled features and trained with multi-perception neural classification (MPNN). The proposed system produces higher forecasting by prediction features as well supportive to the weather dependences related to higher classification rate in precision, and recall has the best classification result.

Keywords— Deep learning; Mutual invariance; feature selection; classification; weather prediction forecasting model; successive weather rate.

I. INTRODUCTION

Human society has tremendous influence by various factors from environmental and social entities. The growing population of world human society introduces multiple challenges for the administrative sector of any country. However, the people of any country grow; meeting the food requirement is a great challenge for the administrative society. As the population grows, the necessity for food commodities also grows. But in reality, the cultivation area is getting reduced due to the growth and extension of residential and industrial sectors, which occupies the agricultural lands. Also, on the other side, the changing environmental conditions affect the rainfall every year, and it's getting reduced. Similarly, the growing industries introduce much pollution to the environment in different ways like air pollution, water pollution, etc. However, to meet the requirement of human society, it is necessary to find some ways to grow the agricultural sector.

Apart from environmental and social factors, other issues can be identified that challenge the agricultural sector's growth. This way, selecting a particular plant for cultivation at the right time makes the difference. For example, choosing a cotton plant for cultivation during the rainy season will give you a different yield than what you expect. Similarly, the onion plant cannot be cultivated in the same period because the growth and yield of any plant depend on the water being poured and temperature as well as humidity conditions, so the selection of plant makes a massive difference in achieving a higher outcome.

To identify the plant that needs to be cultivated, several approaches are available. Some methods use rainfall and temperature as crucial factors in determining plant selection. Similarly, there is an approach which uses few other features in the selection of plants. However, identifying the plant and selecting features is performed with a small set of traces. To increase the performance, it is

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necessary to use a considerable trace of big data. The more supportive plant can be identified by analysing the big data of weather dynamics with agricultural features.

Identifying the suitable plant and recommending a set of options is a big challenge because monitoring the crop and yield required is necessary. The existing approach needs to consider the crop and yield obtained. This paper proposes a novel time variant big data analytics model with multi perception neural classifier to handle all these. The method analyses the big data agriculture data set to extract various features like rainfall, water poured, temperature, humidity, cultivation area, crop, and yield obtained. The contribution and estimation based on the Contemporary Forecasting rate (CFR) for predicting the previous deficiency rate. Based on that Time stamp feature analysis (TSFA). The Dense region harvest rate (DRHR) was evaluated, and features were decision using Fuzzy intensive decision Function (FIDF), selected the scaled features and trained with multi-perception neural classification (MPNN). Accordingly, crop prediction can be performed to estimate the yield value. By calculating the yield effectively, recommendations can be generated to perform plant selection.

The article is organised to present a detailed introduction in Section 1, and Section 2 details the literature survey. Section 3 details the implementation of the proposed approach, and Section 4 details the evaluation results. Finally, Section 5 details the conclusion of the article.

II. RELATED WORK

Weather forecasting has been considered a problem in physics theory for decades, and meteorologists have been working to recover the correctness of predicting by understanding the physical mechanism [1]. With the explosive development of meteorological data from many sources, many dimensions and many scales, it has become commonplace for large spatial data [2].

The DL approach, which is automatically extracted, is more appropriate. Understand the system better. In [3] [4], a weather prediction model is presented, using soil quality, rainfall, and environmental conditions to estimate the yield. In [5], the author presented a plant management model that considers soil and fertiliser quality in increasing cultivation. Determining fertilisers and amendments are the steps towards improving the cost efficiency of the cultivation process [5] [6]. The main environmental factors, like temperature, soil level, and rainfall, define the concentration of minimum intergrading prerequisite for supreme plant development [7]. Most crop-recommending features require more complex information fusion techniques for feature detection [8],

In [9] [10], the application of a neural network with a decision tree in classification has been analysed towards the price of fertiliser and other agriculture products [11]. The learning method to intent measuring crop yield forecasting structure is a new system called precision built for agriculture [12].

Deep neural networks (DNNs) are a type of multi-layered ANN that reconstructs source datasets to analyse the non-related features to reduce the dimension. Similarly, instead of manually selecting a function, a neural network (NN) can "learn" the process [13] [14].

Continuous neural networks (RNNs) are primarily organised to predict the time series weather dataset to forecast the result. Large datasets that cannot be viewed simultaneously can be processed in stages using RNNs [15] [16]. However, standard RNNs are well known for slope collapse and bursts, which makes training difficult, especially if you are accustomed to problems involving long-term dependencies. Most RNNs have only two or three layers compared to deep CNNs, with more than 100 layers.

Weather supports crop production requirements of systems other than crop yield predictions, ultimately leading to a framework that can handle forecasting accuracy [17]. In this work, the author uses various data processing algorithms such as naive Bayes and ANN to forecast the analysis of soil data class [18]. The classifier compilation algorithm examines its accuracy, integrates the remaining classifiers, and removes the classifier that the weekly group learning can use to evaluate its performance. Classifiers can also be selected using more precision and alternate selection.

Since typhoons are tropical, solid meteorological processes affected by many related weather characteristics which are used to analyse the local environment, convulsive neural networks attained the feature reduction concepts to reduce the feature dimensionality using pre-processing [19]. The combination of front-to-back-to-back networks and shallow-to-deep operations have removed restrictions on synthetic functions, and convolutional neurological networks have become an intermediate field in current centuries. Adaptive ANN has been used in many areas of weather forecasting [20]. It is also beneficial for extreme weather forecasts.

All the abovementioned approaches need better performance in classifying and predicting crop and yield.

III. TIMESTAMP FEATURE VARIATION-BASED WEATHER PREDICTION

The forecasting predicts the up comes supportive dataset measures belonging to the dataset based on the

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feature selection and classification. So time variation-based big data analysis is vital for research improvement. To resolve this problem, we propose a Timestamp feature variation-based weather prediction using multi-perception neural classification (TFV-MPNC) for successive crop recommendation in big data analysis. Initially, the pre-processing was carried out to prepare the redundant noise dataset for fast. prediction.

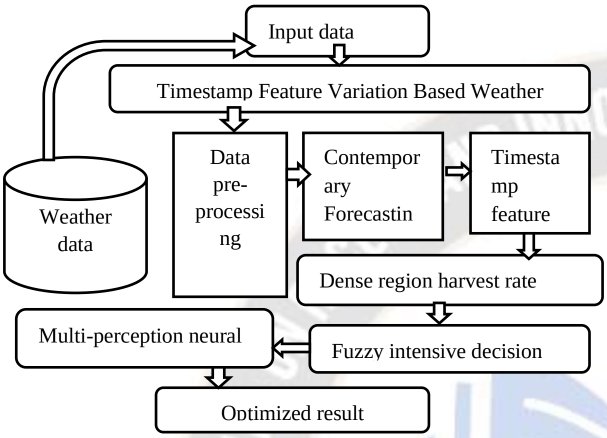

Figure 1: Proposed architecture diagram TFV-MPNC

The critical features observed using the optimised fuzzy model with DNN detect unwanted information on soil and meteorological data and obtain measurable yield predictions. Fig. 1 shows the proposed architecture diagram TFV-MPNC. The seasonal atmospheric data is input as meteorological characteristics. Initially, the proposed system intakes the weather dataset to verify the dimension and range of the feature values and also demonstrates the presence of all feature attributes to create a label index to reduce the size of the dataset. The testing and training data were used to train the sample train database and to test the sample prediction with unknown data to verify the accuracy of the sample predictions. This successive feature rate chooses the success rate of yield from the support values, reducing the dimension defect and the feature dimension ratio for particular input features. This take is carried out from the low dimensional support to the input values.

A. Contemporary Forecasting rate (CFR)

In this stage, the weather data logs are analysed to extract the present rate of feature value present in the current situation. This predicts the maximum threshold based on average mean depth values observed for current weather features present for support crop production.

The data samples are randomised as feature values X = X1, X2 m) and n Observations O = (O1, O2 n. Denote Xnm at regular intervals m. $X_j = ([\underline{x_{1j}}, \overline{x_{1j}}], [\underline{x_{2j}}, \overline{x_{2j}}], \ldots, [\underline{x_{ij}}, \overline{x_{nj}}])'$ to choose the feature margin based on actual and real values'n'

At time series data approximation

$O_i = ([\underline{x_{1i}}, \overline{x_{1i}}], [\underline{x_{2i}}, \overline{x_{2i}}], \ldots \ldots [\underline{x_{mi}}, \overline{x_{im}}])'$ to monitor real data weather index with $x_{ij} = (\overline{x}_{ij}, \underline{x}_{ij})$, so the actual index gets the absolute mean rate to point the real and actual data,

$$x_{ij}\,(\overline{x}_{ij}, \underline{x}_{ij}) \quad (1)$$

The absolute average value variable X_j as

$$E(X_j) = \frac{1}{n}\sum_{i-1}^{n} E(x_{ij}) \quad (2)$$

Where the $E(x_{ij})$ is defined as

$$E(x_{ij}) = \int_{\underline{x_{ij}}}^{\overline{x_{ij}}} s \cdot \frac{1}{(\overline{x_{ij}} - \underline{x_{ij}})} ds = \frac{1}{2}(\overline{x_{ij}} + \underline{x_{ij}}) \quad (3)$$

Definition4

In regular time series interval X_m, is estimated by,

$$\|X_j\|^2 = \sum_{i-1}^{n} \|X_{ij}\|^2 \quad (4)$$

Where

$$\|X_{ij}\|^2 = \int_{\underline{x_{ij}}}^{\overline{x_{ij}}} s^2 \cdot \frac{1}{(\overline{x_{ij}} - \underline{x_{ij}})} ds = \frac{1}{3}(\underline{x}_{ij}^2 + \underline{x_{ij}}.\overline{x_{ij}} + \overline{x}_{ij}^2) \quad (5)$$

Based on several definitions, we have

$$cov(X_j, X_k) = \frac{1}{n} \langle X_j, X_k \rangle \quad (6)$$

$$S(X_j) = \frac{1}{n} \|X_j\|^2 = 1/n\, \langle X_j, X_k \rangle \quad (7)$$

From maximum iteration, the definitions are carried out at regular intervals by the mean of secondary levels. The representations of the covariance lattice behind the Xnm are X (n, m)→ n(Ts). This forecasting rate estimated the absolute rate of the previous dependencies of support rate, which belongs to the current seasonal attribute feature values.

B. Time stamp feature analysis (TSFA)

In this stage, the time variation in weather modulation was analysed. This predicts marginal frequency depending on the time factor. This marginalises the feature variation limits and feature relation intensive rate for crop production for specified intervals. From the big

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Data agriculture data set, the method first identifies the set of agricultural and weather features. From the features identified, the traces of the data sets are verified for the presence of all the features. If any of the features are unavailable, it has been considered incomplete and removed. Further, the method splits the traces into different time stamps, and the feature with any trace identified with no value has been optimised to replace it with a mean value. By computing the mean value of any feature, the traces with missing values are returned to make it complete. Such normalised traces are used towards training to support weather prediction and plant selection.

TVFA Algorithm:

Given: Big Data Agriculture Trace BDAT

Obtain: Preprocess Trace Set PTs.

Start

Read BDAT.

Time set Tws = $\sum_{i=1}^{size(BDAT)} Tws \cup (BDAT(i).Timestamp \ni Tws)$

Feature Set Fs = $\sum_{i=1}^{size(BDAT)} Fs \cup (\sum Features(BDAT(i)) \ni Fs)$

For each timestamp, Ts

For each trace T

If BDAT (TS (T))$\in \forall Features(Fs)$, then

Clear

Else

Tws(Ts) = BDAT(Ts)$\cap T$

End

End

For each Trace T

For each feature f

If Ts(T(f))==Null then

Ts(T(f)) = $\frac{\sum_{i=1}^{size(BDAT)} BDAT(Tws(Ts)(T(f))}{size(BDAT(Tws(Ts))}$

End

End

End

PTS (Ts) = BDAT (Ts)

End

Stop

The above-discussed algorithm applies a time-variant feature analysis algorithm for pre-processing, which identifies the noisy record and applies normalisation on the feature identified with the null value. Further, the traces are split based on the time stamp and used to perform MPNC Training.

C. Dense Region Harvest Rate (DRHR)

The harvest rate was estimated based on the CFR and TSFA prediction rates. This compares the successive historical production to the previous history and recommends cultivating the crop for a certain amount. This selects the features relevant to the specific region's crop production yield rate. This chooses the success rate from the maximum yield harvest rate, which the higher values support from the particular features. This formalises the maximum success rate formed by the collective mean feature rate. Crop Achievement Support (CAS) Estimation:

Crop achievement support is the measure which represents the support provided by the features of environmental and agricultural features in achieving higher crops of plants. Various factors of agricultural and environmental entities decide the plant's yield. For example, consider the temperature T, one of the ecological features that can be approximated in measuring the value of CAS by computing the value of the Weather Crop Impact Factor (WCIF). Similarly, the humidity feature also can be used in calculating the value of WCIF. On the other side, the value of the area of cultivation number of industries has been used in measuring the value of the Environmental Crop Impact Factor (ECIF). The features of rainfall and water poured have been used in calculating the value of the Hydro Crop Impact Factor (HCIF). Using all these features and impact factors, the method would compute the value of CAS for various plants.

CAS Estimation Algorithm:

Given: Time stamp trace Tst, Plant Type Pt, Trace T

Obtain: CAS

Start

Read Tst, Pt, T.

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Find the traces of plant as PTs = $PTS \cup (\sum_{i=1}^{size(Tst)} Tst(i).Type == Pt)$

Compute Weather Crop Impact Factor WCIF = Dist(T.Temp,$\frac{\sum_{i=1}^{size(PTS)} PTS(i).Temp}{size(PTS)}$)× Dist(T.Humidity,$\frac{\sum_{i=1}^{size(PTS)} PTS(i).Humidity}{size(PTS)}$)

Compute Environmental Crop Impact Factor ECIF = Dist(T.AC,$\frac{\sum_{i=1}^{size(PTS)} PTS(i).AC}{size(PTS)}$)× Dist(T.NoI,$\frac{\sum_{i=1}^{size(PTS)} PTS(i).NOI}{size(PTS)}$)

//where AC – Area of Cultivation, NoI – Number of Industries

Compute Hydro Crop Impact Factor HCIF = Dist(T.RF,$\frac{\sum_{i=1}^{size(PTS)} PTS(i).RF}{size(PTS)}$)× Dist(T.Wp,$\frac{\sum_{i=1}^{size(PTS)} PTS(i).Wp}{size(PTS)}$)

// where WP – Water Poured, RF – Rainfall.

Compute CAS = WCIF×ECIF×HCIF

Stop

The above-discussed algorithm computes the value of CAS by estimating the crop impact factor related to various constraints. Based on the importance of WCIF, ECIF and HCIF, the method adds the value of CAS. Similarly, yield achievement support is the measure which represents the name of the plant, which would produce more yield at the available weather condition and other environments and hydrology conditions. Given a sample of agriculture trace with a set of features, the method can compute the YAS value based on the impact of different elements like weather, hydrology and environmental conditions. The method calculates the Weather yield achievement support (WYAS) based on temperature and rainfall values. Similarly, the value of Environmental Yield Achievement Support (EYAS) is based on the area's features of the area of cultivation and the number of industries. Also, the Hydro Yield Achievement Support (HYAS) is measured based on hydro elements like rainfall and water poured. Using all these values, the method computes the value of HYAS.

HYAS Estimation Algorithm:

Given: Time stamp trace Tst, Plant Type Pt, Trace T

Obtain: YAS

Start

Read Tst, Pt, T.

Find the traces of plant as PTs = $PTS \cup (\sum_{i=1}^{size(Tst)} Tst(i).Type == Pt)$

Compute Hydro Yield Impact Factor HYIF = Dist(T.RF,$\frac{\sum_{i=1}^{size(PTS)} PTS(i).RF}{size(PTS)}$)× Dist(T.Wp,$\frac{\sum_{i=1}^{size(PTS)} PTS(i).Wp}{size(PTS)}$) $\times\frac{1}{\sum_{i=}^{size(PTS)} PTS(i).Yield / size(PTS)}$// where WP – Water Poured, RF – Rainfall.

Compute YAS = WYIF×EYIF×HYIF

Stop

The above-discussed algorithm measures the Yield Achievement Support (YAS) value by computing different yield impact factors produced by various weather, environment and hydrology features. Using the impact factors of various class features, the method computes the values of Yield Achievement Support (YAS). The estimated value of YAS has been used in plant selection and recommendation generation.

D. Fuzzy Intensive Decision Function (FIDF)

In this stage, the logical conditions are ruled out with fuzzy membership. This creates a set of normalised rules for selected feature rates from CFR, TSFA, and FIDF rates. This decides to group the feature values for the suitable recommendation. The fuzzy set determines the features based on regular interval-valued data that can be treated as assets created by the fuzzy membership function boundary of margins. Therefore, given interval–valued variables $X_1, X_2, \dots \dots . X_m$ Each variable has n observation,$e_j \in R, j = 1,2, \dots .$m. the interval-valued PC score Y_k is undeviating grouping $X_1, X_2, \dots \dots X_m$

$$Y_k = \sum_{j-1}^{m} e_j X_j = \left([\underline{y_1}, \overline{y_1}], [\underline{y_2}, \overline{y_2}] \dots \dots \dots \dots [\underline{y_n}, \overline{y_n}]\right)' \quad (8)$$

Where

$$\underline{y_i} = \sum_{j-1}^{m} e_j \left(\tau \underline{x_{ij}} + (1-\tau) \overline{x_{ij}}\right) \quad (9)$$

$$\overline{y_i} = \sum_{j-1}^{m} e_j \left(1-\tau\right)\underline{x_{ij}} + \tau\overline{x_{ij}} \quad (10)$$

$$\text{With } \tau = \begin{cases} 0, & a_j \le 0 \\ 1, & a_j > 0 \end{cases} \quad (11)$$

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K==(1,2,….m) let (e_v, λ_v) $with$ $e_{v=(e_{v1},\ldots\ldots e_{vm})}$ v=1,…..,m and be the eigenvectors eigenvalues of Σ.the Eigenvector connected with the eigenvalues. This is because the total variance is $\sigma^2 = \sum_{j=1}^{m} \lambda_j$ b, formed by the principal mean average value.

The progressive steps are,

Step 1: Create time services interval difference matrixX_{nm} .

Step 2: Computed correlation matrix formed deceive function ofX_{nm} .

Step3: compute the eigenvectors $e_1, e_2, \ldots \ldots e_m$ $(s \leq m)$and the eigenvalues$\lambda_1 \geq \lambda_2 \geq, \ldots \ldots \ldots \lambda_m$.

Step4: compute the principal component $Y_1, Y_2, \ldots \ldots \ldots \ldots, Y_m$

The attribute feature selection is proposed for the interior focuses.

- The property of each attribute factor chooses the evaluation features which remain in the successive iteration to improve the closer value on marginal spectral values.
- The time series average margin that observes the training algorithm's closest features is illustrated below.
- Timestamp transition table construction remains the Regular interval variation
- Imaginary features base points B on fuzzy set compute as

  $E(w + \Delta w) = E(w) + E'(w)^T \Delta w +$
  Δ (Remain reflection)$w^T E''(w)\Delta w$ (12)
- Computes marginal bounded values B = E'(w) and C = E″(w) are reflected values to the features.
- The remains C is the Transition matrix and gradient features on repeated values
- Compute the sum of all closest values remains the transient search Seasonal feature representation has remained Upper Max-Min to the lower membership values

  $The\ E\ remains\ subset\ rules\ of\ weightage\ E(w + \Delta w) = E(w) +$
  $B^T \Delta w + \Delta w^T C \Delta w$ (13)
- The quadratic referential On w remains the solution
- $\Delta w = C^{-1}B$ (14)
- Return weightage to node

The scaling factors remain the range of particular points in random quadratic facts of weightage with subset features. The Max features of weightage need the value of the feature count on marginal values with average mean weightage to significantly assign to the neural based on the Min value to all the nodes. This selects the logical decision during the membership function and creates logical representation by defining by structural mean of average feature set values for input to the classifier.

E. Multi Perception Neural Classifier (MPNC)

This classifier is based on an adaptive kernel model in a deep neural network with soft-max activation logical neurons. This densely converts the fuzzy rules into a training function. The threshold values are fixed to predict the class for active comparison of the feature margin rate. This classifier initiates the kernel model and forwards the spectral feature points to the internal layer, where the neurons at the layer estimate Crop Achievement Support (CAS) and Yield Achievement Support (YAS) to measure the Cultivation Weight (CW) for specific plants. The output layer receives the CW value of the k number of plants according to the number of intermediate layers or the number of plant classes considered. Now the method gets the output set and ranks the plants according to the CW value of various categories of plants. Fig. 2 defines the multi-perception neural classifier,

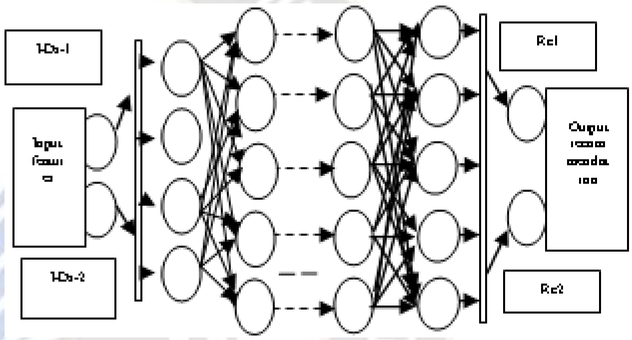

Figure 2. Multi-perception neural classifier

Time redundancy in this technique runs from one layer output to layer input, running unnoticed before training. The first inertial car encoder (1st middle layer) has the source input (x) tutorial to know the primary function. The retainable dense features of the next hidden layer are ordered to autocorrelation function to adjust all weight features at minimum search feature relevance.

MPNC Classifier Algorithm:

Given: Neural Network NN, Feature Vector F.

Output: Recommendation

Start

Read neural network NN, Feature Vector F.

For each layer

For each Time stamp Ts

Neuron Estimates CAS and YAS.

Neuron Estimates CW for Plant P (Layer) =CAS×YAS.

End

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End

Receive CW set in the output Layer.

Sort plants according to CW.

Generate recommendations with the sorted list.

Stop

IV. RESULTS AND DISCUSSION

The proposed Time Variant Big Data Analytics Model Based on Weather Prediction and plant selection model has been implemented in Matlab. The method's performance has been evaluated under various performance metrics using an agricultural data set collected from the region's Agricultural Research India (ARI) department. This section compares obtained results with the results of different other approaches.

TABLE I. Details of Evaluation

Parameters used	**Values processed**
Dataset used	Crop yield dataset (ARI)
Simulation environment	Mat lab
Number of attributes	15
Number of Class	10 (Types of Plants)

The details of the data set and features considered for the performance evaluation have been presented in Table 1. According to this, the method's performance has been measured and compared with the results of other approaches as below.

A. Accuracy

The performance of methods is measured for their classification accuracy. It has been estimated based on the number of true negative and actual positive classifications generated correctly with the total number of categories performed. It has been estimated as follows:

$$\text{Accuracy} = \frac{TN+TP}{(TP+FP+FN+TN)} \qquad (15)$$

TABLE II. Analysis of Classification Accuracy

Methods /dataset records	**Impact of Classification Accuracy in %**			
	SVM	**PLC**	**DTC**	**TFV-MPNC**
100	87.3	91.1	93.1	94.6
500	89.5	92.2	93.6	95.2
1000	91.3	92.7	93.8	95.9
2000	92.1	92.5	94.2	96.8
3000	92.6	92.9	94.2	97.9

The accuracy of classification made by various approaches at the availability of different records in the data set has been measured and presented in Table 2. The proposed TFV-MPNC has produced higher performance in classification than other approaches.

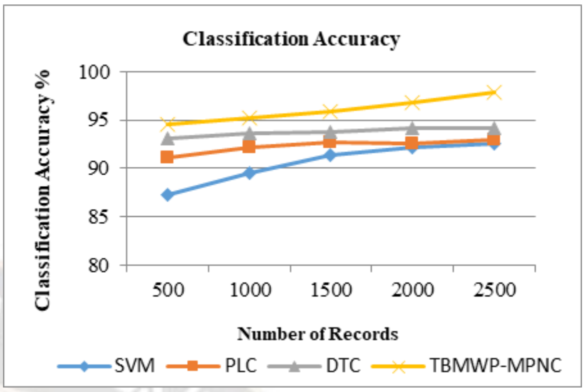

Figure 3: Analysis of Classification Accuracy

Fig. 3 explores the analysis of classification accuracy performance. The performance proposed method in classification accuracy has been measured with the different number of records at each class. In all the cases, the proposed TFV-MPNC algorithm has produced higher performance than other approaches. The performance of the approach is compared with SVM (Support Vector Machine), PLC, and DTC (Decision Tree Classifier).

B. False Ratio

The ratio of false classification produced by various approaches is measured and presented in this part. The false ratio has been calculated by computing the number of false categories made among the number of types performed.

$$\text{False ratio} = \frac{\text{False Positive} + \text{False Negative}}{\text{Total Classifications}} \qquad (16)$$

TABLE III. Analysis of False Classification Ratio

Methods/Datasets records	**Impact of False Ratio in %**			
	SVM	**PLC**	**DTC**	**TFV-MPNC**
100	13.3	8.9	6.9	5.4
500	11.5	7.8	6.4	4.8
1000	8.7	7.3	6.2	4.1
2000	7.9	7.5	5.8	3.2
3000	7.4	7.1	5.4	2.1

The method's performance in producing false classification has been measured and presented in Table 3. The proposed TFV-MPNC approach has made less false ratio than other methods.

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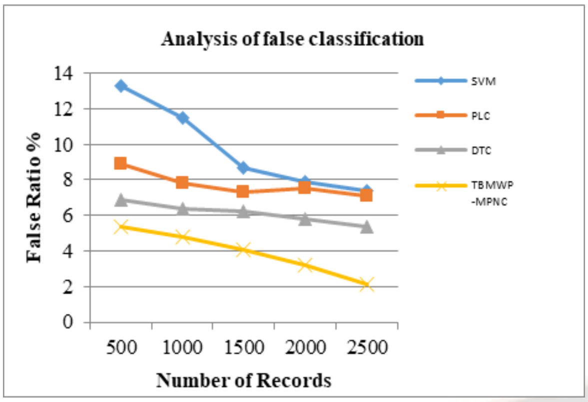

Figure 4. False Ratio Analysis

Fig. 4 explores false rate analysis result performance. The performance of methods in false classification is measured and compared with the results of other methods. The proposed approach has produced less false ratio compared to different approaches.

C. Time Complexity:

The performance of methods is measured on the time complexity, which is based on the value of total time taken and the number of features handled. It has been estimated as follows:

Time complexity (Tc) =

$$\sum_{k=0}^{k=n} \times \frac{\text{Total Features Handeled to Process in Dataset}}{\text{Time Taken}(Ts)} \quad (17)$$

TABLE IV. Performance of time complexity

Methods/Datasets records	Impact of Time Complexity in Milliseconds (ms)			
	SVM	PLC	DTC	TFV-MPNC
100	86.7	87.1	88.3	78.6
500	88.5	88.6	89.6	82.3
1000	89.3	89.2	89.8	85.7
2000	89.4	91.2	91.2	87.2
3000	90.3	91.5	92.2	89.6

The performance of different methods at their time complexity in classification has been measured and presented in Table 4. The proposed TFV-MPNC algorithm has produced less time complexity than other methods.

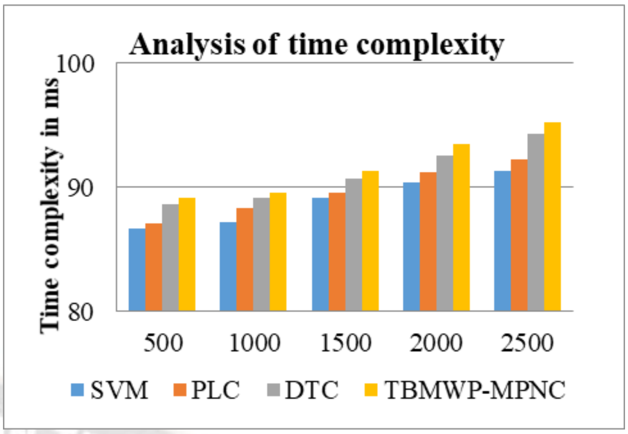

Figure 5. Analysis of Time Complexity

Fig. 5 shows the time complexity for crop recommendation using the proposed method. The performances of methods are measured for their time complexity in classification. The proposed TFV-MPNC algorithm has produced less time complexity in each case than other approaches. Complex time is calculated in milliseconds. The lower limit of processing the O (N) command in any sign code is if it has any sign to reveal the upper side. In its worst form of calculation, the average bound is G (n), and the mean intermediate boundary is F (n), which can be taken to account for the average time. The proposed proves the implementation of neural classification produced higher efficiency results in crop datasets trains and tested reveals the accuracy.

V. CONCLUSION

To conclude, the proposed weather forecasting model produces higher performance than the other existing system. As well, classification accuracy significantly impacts precision-recall by handling lower time to predict and forecast the result. The Timestamp feature variation extracts the particular features depending on the time-variant seasonal representation then the classifier attains the weather prediction using multi-perception neural classification to train the neural network, which produces a successive crop recommendation to reduce the dimension in big data analysis. The proposed system has higher performance as well in weather prediction. The results prove the confusion matrix produces the testing and training validation higher impact in accuracy in sensitivity, making 94.3 and specificity have up to 95.1%, F- measure produces a 6.4% high resultant level compared to the prior methods. The overall rate of weather prediction rate is higher in classification accuracy, up to 96.3%, compared to the other methods.

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