J. Electrical Systems 20-7s (2024): 3003-3015

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Construction and Application of Agricultural Economic Audit Model Based Big Data Analysis

Journal of Electrical Systems

Abstract: - In the economic audit model based big data analysis of construction and application of agricultural economic audit. Plant pests are a major global danger to agricultural productivity because of how intense and extensive their outbreaks are becoming. Unfortunately, lesion image segmentation techniques used in the past to identify these pests are laborious and ineffective, making it difficult to generalize and implement the research's conclusions. This manuscript presents construction and application of agricultural economic audit model (AEAM-VONN) is proposed. Initially, the data is collected from Distributed Denial of Service attacks (DDos) data, in CIC NIDS datasets, IDS2019. Afterward, the data's are fed to pre-processing. In pre-processing segment Cubature Kalman Filtering Method (CKFM) is used to clean the data. The pre-processed data are given into Adaptive Synchro Extracting Transform (ASET) and which is used to extract the features such as spectral indices, textural features, zonal statistics, plot boundary extraction, mosaicking. The extracted features from ASET are transferred to the Variational Onsager neural Network (VONN) for classification. The VONN method effectively classifies Binary classification and Multi class classification. The Botox Optimization Algorithm (BOA) is used to optimize the weight parameter of VONN. The proposed approach is implemented in Python, and several performance metrics, like precision, recall, accuracy ,FAR, F-score, and computation time, are used to measure the proposed (AEAM-VONN) method's efficiency.. Proposed AEAM-VONN method attains higher accuracy 89.80%,FI-Score 59.99%, higher precision0.3% and higher recall 68.90% for highly credible analyzed to the existing methods, like A Novel Deep Learning Models for Efficient Insect Pest Detection and Recommending an Organic Pesticide for Smart Farming(NDLM-EIPD-APSO), A Software Toolkit to Empower Precision Agriculture with GeoAI(STEP-AGAI-DNN) Research on Digital Communication Mode of National Traditional Sports Culture Based on BP Neural Network Prediction of DDoS attacks in agriculture 4.0 with the help of prairie dog optimization algorithm with IDSNet (PDA-PDO).

Keywords: Intrusion Detection System, Botox Optimization Algorithm, Agriculture 4.0, Deep Learning Approaches, Ddos Attack, Smart Agriculture Section System, Variational Onsager Neural Network.

I. INTRODUCTION

The Construction and Application of Agricultural Economic Audit Model Based on Big Data Analysis. These technologies connect machines to the Internet through the Internet-of-things, allowing for the collection of data in the Cloud and Edge and subsequent processing of that data using artificial intelligence algorithms [1]. The goal is to optimise operations and reduce costs. A fundamental requirement for human survival is agriculture. Population growth is always putting strain on resources to feed the expanding population Resources and food production management are necessary to feed the expanding population [2]. Numerous variables, including weather, water, soil quality and type, and irrigation management, affect agricultural productivity. A fundamental requirement for human survival is agriculture. Population growth is always putting strain on resources to feed the expanding population [3]. Management of food production and resources are required to feed the expanding population. In an effort to increase crop yields, farming has been more intense. We need smart agriculture if we are to generate enough food. Agriculture becomes more precise and forecast with the use of satellite data. In order to meet the requirement for food, smart farming has undergone significant evolution in recent years [4-6] .When it comes to the soil's pH values, a farmer should increase ammonium intake if the pH rises significantly, and decrease ammonium input if the pH decreases [7].In agriculture, solutions are frequently utilized due to the numerous benefits they provide to farmers. A number of assaults were made possible by the interconnectivity of various sensors and network devices. This is due to the fact that such devices usually have out-of-date or unpatched firmware or software [8, 9]. Federated transfer learning is suggested as a means of classifying rice-leaf disease across multiclient cross-silo datasets. The paper discusses the challenges associated with group learning in agriculture. It encourages a federated strategy. This contribution is crucial for situations when datasets are dispersed among multiple sources, as it enables the parties to train models collaboratively without

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requiring the centralization of sensitive data [10-12]. To tackle the afored mentioned concerns and exert pressure on the agriculture industry, it is imperative to maximize the efficiency of agricultural procedures while also reducing the impact on the environment. Specifically, the development of precision agriculture has been fueled by these two necessities [13-15]. Modern farming has a lot of promise to ensure environmental safety, maximum productivity, and sustainability [16-19].

In order to alleviate the pressure on the agriculture sector caused by the aforementioned challenges, it is imperative that agricultural techniques be optimized while also reducing their environmental impact. Specifically, the development of precision agriculture has been fueled by these two necessities. Modern farming has a lot of promise to ensure environmental safety, maximum productivity, and sustainability. A significant barrier to extracting valuable insights from field data is the limitations of traditional data processing methods in meeting the ever-rising needs of the fresh era of smart agricultural technologies.

The following is a summary of this research work's primary contributions:

- At first, the data are gathered via the data of Distributed Denial of Service attacks (DDos) data.
- Using anun sharp structure guided filtering to clean the data at DDos data in the pre-processing segment.
- The pre-processed data are fed into the Variational Onsager Neural networkto effectively clsssifies the as binary and multiclass.
- Performance measures including accuracy, precision, true negative rate ,sensitivity, specificity, recall, are used in the implementation of the proposed AEAM-VONN approach.

II. LITERATURE SURVEY

Many research works were suggested in the literature related to deep learning The Construction and Application of Agricultural Economic Audit Model Based on Big Data Analysis.

Yards and Dener [20] have recommended utilising PySpark with Apache Spark in the Google Collaborator (Colab) environment to analyse the acquired network traffic dataset in a big data environment and identify network assaults using a deep learning algorithm. ‘The "TON_IoT" and "CICIoT2023" datasets are utilised to train and evaluate the model. The correlation approach ensures that meaningful characteristics are included in the tests by reducing the number of features in the datasets. It provides high F1 measure and it provides low accuracy.

Al-Quayed et al. [21] have suggested these networks are always gathering data and streamlining procedures, they are always open to cyber attacks. People are more vulnerable to cyber attacks as a result of increased connections, thus using robust cyber security measures to safeguard sensitive data is essential. It provides high F1 measure and it provides low accuracy.

Vatambeti et al. [22] have suggested the issues with cyber security that Agriculture faces, as well as the metrics used to rate intrusion detection systems' efficacy. To analyse intrusion detection systems in the context of upcoming and present technological advancements, including industrial agriculture, drones, autonomous tractors, smart grids, and the Internet of Things. It offers a low F1 measure and strong recall.

Talukder et al. [23] have suggested the Collectively sensing, collecting, processing, and transferring data about their environment, these sensors self-organize and form multi-hop links for communication. WSNs undergo frequent and harmful assaults that might impair operation despite their importance..It provides low error rate, and it provides low recall.

Saxena et al. [24] Have suggested , evaluated, and shown accuracy using k-fold cross-validation, ensuring robust performance across different subsets. Enhancing stakeholder knowledge, straightforward displays interpretability and prioritisation. For this research, inclination relief techniques, security shields, and moral reflections are essential. It delivers low F1 measure and great precision.

Jhajharia et al. [25] have suggested The agricultural domain's subcategories that have been noted are crop yield prediction, soil management, insect control, weed management, and crop disease. The results show that machine learning offers superior classification or regression accuracy. Researchers are motivated to focus onsmart. Farming and food security by machine learning which has developed with the internet of things, drones, robotics, automated machinery, and satellite photography. It provides high precision, and it provides low F1 measure.

Benos et al. [26] have suggested carefully evaluating recent scholarly literature based on keyword combinations that include "machine learning" together with "crop management," "water management," "soil management," and "livestock management," the current study seeks to shed light on machine learning in agriculture. It provides high accuracy, and it provides low F1 measure.

III. PROPOSED METHODOLOGY

In this section, Variational Onsager Neural Network along with Botox Optimization Algorithm (VONN-BOA) is proposed. Block diagram of proposed Methodology is presented in Fig 1. This process consists of five steps: Data Acquisition, pre-processing, classification, and optimization. The data's are fed to pre-processing. In pre-processing segment Cubature Kalman Filtering Method (CKFM) is used to clean the data. The pre-processed data are given into Adaptive Synchro Extracting Transform (SET) and which is used to extract the features such as spectral indices, textural features, zonal statistics, plot boundary extraction, mosaicking. The outcome from the pre-processing data is transferred to the Variational Onsager neural Network (VONN).The VONN method effectively classifies Binary classification and Multi class classification. The Botox Optimization Algorithm (BOA) is used to optimize the weight parameter of VONN. As a result, a thorough explanation of each step is provided below.

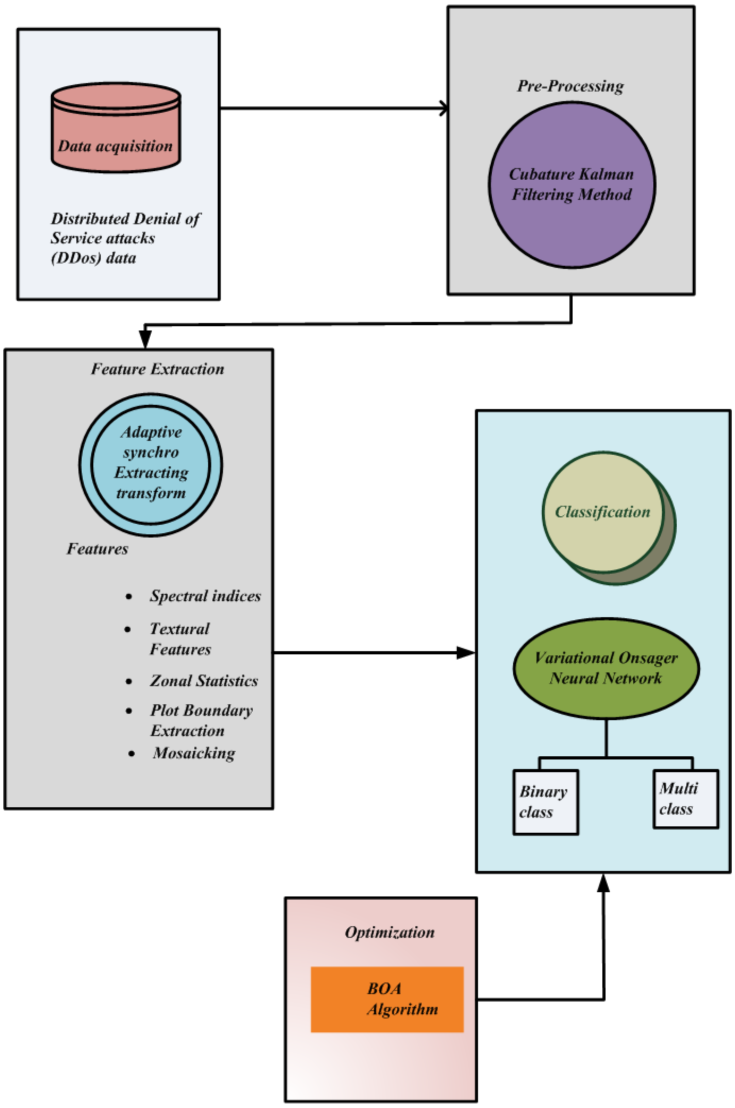

Fig 1: Block Diagram for Proposed Methodology

A. Data Acquisition

This is an academic intrusion detection dataset [27]. An expanded collection of DDoS assaults is provided by the dataset, the majority of which use amplification through reflection. The feature set of the dataset is shared with IDS2019, another CIC NIDS dataset.

B. Preprocessing using Cubature Kalman Filtering Method (CKFM)

The CKFM accounts for the error information lost during the CKF sampling approximation to the real value in the state estimation process in order to optimise the utilisation of the information from the nonlinear system state model and nonlinear observation model. Consequently, the CKFM may get higher estimate accuracy.
Set the state quantities to initial values and calculate the error covariance:

$$X|(0/0) = E\{x(0)\}| \tag{1}$$

$$P(0/0) = E\{[x(0) - x(0/0)][x(0) - x(0/0)]^T\} \tag{2}$$

The point set has a entire of 2N points, where $n(X) = 1i(k)02ni = 1;$ is a sample point that was collected via sampling. To create the point set, establish a collection of sigma points under the nonlinear transformation. f (・). Compute the $P(k/k)$ square root matrix after doing the Cholesky decomposition on $P(k/k)$.

$$P(k/k) = S(k/k)S(k/k)^T, S(k/k) = \sqrt{p(k/k)} \tag{3}$$

Generate cubature points with equal weights

$$x_i(k/k) = x(k/k) + s(k/k)\zeta_{i,} i = 1,2,\ldots\ldots 2n \tag{4}$$

At instant k, where ξ^i is fulfilled and $X_i(k/k)$ represents the cubature point of the state:

$$\zeta_i = \sqrt{n} e_{i,} i = 1,2,\ldots.. 2n \tag{5}$$

where n is the state vector's dimension and e^i is the matrix's column vector (5) Determine the sample point's condition Cubature point:

$$x_i(k+1/K) = f(x_i(k/k)) \tag{6}$$

The weighted fusion prediction estimate of $X(k+1)$ is obtained by giving each prediction a weight.

$$x(K+1/K) = \frac{1}{2n}\sum_{i=1}^{2n} x_i(K+1/k) \tag{7}$$

C. Feature Extraction using Adaptive Synchro Extracting Transform

The ASET [28] is a variant of synchro extraction transform algorithm is used for optimization task. In the identification and classification the following features spectral indices, textural features, zonal statistics, plot boundary extraction, mosaicking are usually extracted which can be obtained by computer technology.
The STFT of the signal taking into account an extra phase shift for a particular set of data

$$STFT(t,\omega) = \int_{-\infty}^{+\infty} g(u-t)s(u)e^{-i\omega(u-t)}du \tag{8}$$

where ω is the angular frequency and $g(u-t)$ is a moving time frame. In this context, zonal statistics $STFT$ are used. Let $g_\omega(u) = g(u-t)e^{i\omega(u-t)}$, then using Parseval's theorem, we can rewrite Eq. (7) as follows in the frequency domain:

$$STFT(t,\omega) = \frac{1}{2\pi}\int_{-\infty}^{+\infty} G_\omega^*(\xi)\cdot S(\xi)d\xi \tag{9}$$

$G_\omega(\xi)$ and $S(\xi)$ are represented by the Fourier transforms, $g_\omega(u)$ and $s(u)$, respectively, where * indicates a complex conjugation. After that, we may have:

$$G_\omega(\xi) = \int_{-\infty}^{+\infty} g(u-t)e^{i\omega(u-t)}e^{-i\xi t}du \tag{10}$$

Let $u - t = \tau$, is rewordable as:

$$G_\omega(\xi) = e^{-i\xi t}\int_{-\infty}^{+\infty} G(\tau)e^{-i(\xi-\omega)\tau}d\tau = e^{-i\xi t}G(\xi-\omega) \tag{11}$$

where the moving time window $g(u-t)$'s Fourier transform is represented by $G(\xi-\omega)$. Substituting Eq. (10) into, the STFT of $s(u)$ may be restated as:

$$STFT(t,\omega)=\frac{1}{2\pi}\int_{-\infty}^{+\infty}G(\xi-\omega)\cdot S(\xi)\cdot e^{i\xi t}d\xi \tag{12}$$

Observing that a fully harmonic signal has a Fourier transform of $s(t)=A\cdot e^{i\omega_0 t}$

$$S(\xi)=2\pi A\cdot\delta(\xi-\omega_0) \tag{13}$$

Substituting we have:

$$STFT(t,\omega)=A\cdot G(\omega-\omega_0)\cdot e^{i\omega_0 t} \tag{14}$$

By making a distinction (14) between the amount of time to have:

$$\omega_0(t,\omega)=\frac{\partial_t STFT(t,\omega)}{iSTFT(t,\omega)} \tag{15}$$

Where The two-dimensional instantaneous frequency (IF) is approximated as ω_0.

SET extracts the TF coefficients of $STFT(t,\omega)$ only at the IF trajectory $\omega=\omega_0$ by using a synchro-extracting operator $SEO(t,\omega)=\delta(\omega-\omega_0(t,\omega))$ together with STFT as:

$$SET(t,\omega)=STFT(t,\omega)*SEO(t,\omega) \tag{16}$$

Then the selected features are transferred in to classification phase.

D. Classification using Variational Onsager Neural Network (VONN)

In this section, Fuzzy clustering model using neural network is discussed [29].VONN is used to classify the c-mean of mold paste is used to classify and assess the temporal and weather features while taking sample difference into account. The neural network's input value and normalized sample data operate smoothly in the range of 0 to 1. Adjust the neural network's parameters by changing the training parameters, which include the learning rate, training periods, minimal error, etc., using the normalised sample data and the unique data associated with each sample as input. In order to determine which data require further investigation, make a comparison between the predicted and actual values of the output findings.

$$y_{i+1}=g_i(W_{iyi}+b_i), i=0;\dots\dots\ \dots k, \tag{17}$$

Here , wk_j is the j^{th} neuron's connection weight in the hidden layer.

To determine the most accurate projected value for the following series, a recurrent neural network can learn a probability distribution and maximise that probability.. After passing through many model functions, the input sequence is produced via an encoder-decoder structure. Uneven sequence lengths between the input and output are a possibility. The variable-length sequence's conditional distribution probability can be ascertained by training.

$$y_{i+1}=g_i(W_i^y y_i+W_i^\omega\overline{w}+b_i), i=0,k. \tag{18}$$

This formula shows that each layer of neurons' output function takes on the function. The subject of national economic accounting is a multifaceted system that is susceptible to fluctuations in different causes, including shifts in policy and the external environment. Therefore, to improve the dynamic management and supervision of information, an efficient VO NN neural network model algorithm must be implemented.

$$A_k p(\xi)=0, k=1,\eta PDE_s \tag{19}$$

There is no appreciable divergence from the anticipated mineral product tax value in the forecast value of the product tax prediction model utilising wavelet noise reduction on the tax data; instead, the relative percentage

$$B_k P(\xi)=h(\xi), k=1,\eta_{BCS} \tag{20}$$

It demonstrates how the interference of the noisy data in the original time series with the model prediction is lessened when wavelet transform is applied to the prior data for data demising.

E. Optimization Using Botox optimization algorithm (BOA)

In this segment, Botox optimization is used to eliminate the missing data. As a theoretical research progresses, some academics have developed a novel approach to solving bi-level programming models using Botox optimization [30]. Notion based on pertinent Botox optimization theory. While fuzzy theory offers more benefits for handling the uncertainties of complex water systems, the bi-level programming method is more suited for solving hierarchical challenges in the planning and management of water resources system.

Step1: Initialization

Initialization, the random vectors produce the input parameters at random. It expressed in equation.

$$X = \begin{bmatrix} X1 \\ \vec{X}_i \\ \vec{X}_N \end{bmatrix}_{N\times M} \begin{bmatrix} X_{1,1} & X_{1,d} & X_{1,m} \\ X_{i,1} & X_{i,d} & X_{i,m} \\ XN_1 & X_{N,d} & X_{N,m} \end{bmatrix}_{N\times M} \quad (21)$$

$$x_{i,d} = lb_d + r_{i,d}(ub_d - lb_d), i = 1,........., N, d = 1,......... m,$$

Where X is the BOA population matrix, $\vec{X}_i$ is the i_{th} BOA member $x_{i,d}$ is its d_{th} dimension in the search space N specifies the conut of population members ;m specifies the conut of decision variables, r_{id} are random variables i_{bd} and u_{bd} are the d_{th} decision variable's lower and upper bounds, correspondingly.

Step 2: Random Generation

The input parameters are generated at random after startup. The values of optimal fitness are chosen in this case based on their specific hyperparameter scenario.

Step 3: Fitness Function

Fibre is impacted by the aim function. Equation describes the fitness function as follows:

$$Fitnessfunction = optimizing(\xi, \eta) \quad (22)$$

Step 4: Exploration ξ

The distribution of population members inside the problem space is referred to as the BOA's population diversity, and it is vital for tracking the algorithm's search operations. This measure essentially shows if the population members are centered on discovery or utilization. One way to assess and modify the algorithm's ability to effectively investigate and exploit a collective group is to measure the variety of the BOA population. Scholars have proposed many meanings for diversity.

$$\text{Diversity}= \frac{1}{N}\sum_{1=1}^{N} \sqrt{\sum_{d=1}^{m}(x_{i,d} - \bar{x}_d)^2}, \quad (23)$$

$$\bar{x}_d = \frac{1}{N}\sum_{i=1}^{N} x_{i,d} \quad (24)$$

$$Exploration = \frac{Diversity}{Diversity_{\max}}, \quad (25)$$

Here , m is the count of problem dimensions , N specifies the count of population members and X_d specifies the population's mean overall in the d_{th} dimension. $X_{new}idj$ in the dj_{th} dimension.

Step 5: Exploitatio**n** η

The BOA approach at each iteration provides graphical assistance for examining the way the algorithm strikes a balance between local and global search tactics. With high values in the first iteration and low values in the final iteration, the simulation results show that the demographic diversity of the BOA is favourable. Additionally, the data show that the BOA's exploitation ratio is normally in the neighbourhood. The results of this investigation verify that the suggested BOA strategy performs well in controlling and balancing exploitation and exploration throughout the search process by generating the proper population diversity during algorithm rounds.

$$Exploitation = 1 - Exploration \quad (26)$$

Step 6: Termination

Verify the termination criterion; if it is satisfied, the best possible solution has been found; if not, repeat the procedure.

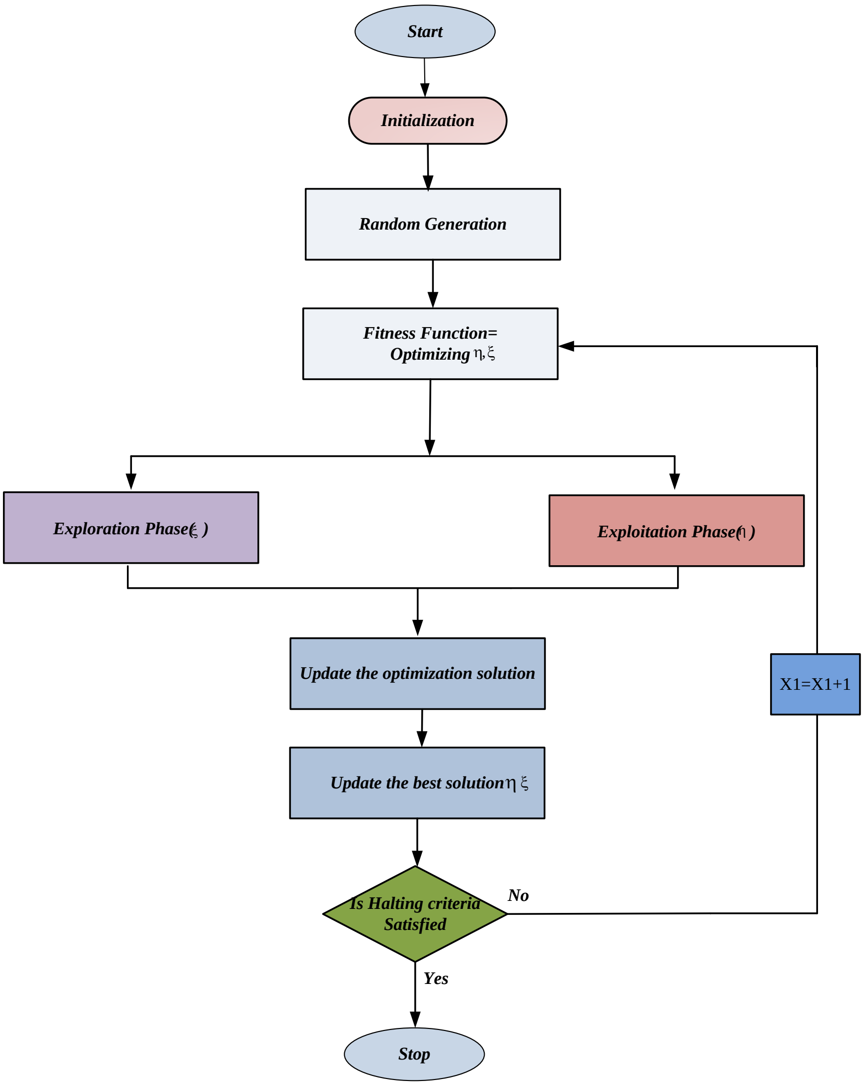

Fig 2: Flowchart of BOA optimizing VONN

IV. RESULT AND DISCUSSION

The experimental findings of the proposed approach are covered in this section. Then, proposed technique is simulated using MATLAB under mentioned performance metrics. Fig 2 shows Flowchart of BOA optimizing VONN.

A. Performance measures

In order to choose the optimal classifier, this is an important task. Performance measures including sensitivity, accuracy, precision, specificity, recall, and computing time are analysed to assess the performance.

1) Accuracy

The capability to measure precise value is called as accuracy. A statistic called accuracy may be used to characterise the model's performance in all classes. The following stated equation is used to measure it.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{27}$$

In this step, True negative is indicated by TN , True positive is indicated by TP, false negative is indicated by FN and false positive is indicated by FP.

2) Precision

Precision estimation include many positive labels had expected with high accuracy, it is given an equation.

$$\Pr ecision = \frac{TP}{(TP + FP)} \quad (28)$$

3) F-Score

It is crucial to select the right performance measures for assessing deep learning and machine learning techniques.

$$F - sore = 2 * \frac{(precision * \operatorname{Re} call)}{(precision + \operatorname{Re} call)} \quad (29)$$

4) Recall

Positive result may be identified by a machine learning model using recall metrics. Otherwise said, it gauges your chances of receiving a favourable outcome. Thus it is given an equation

$$\operatorname{Re} call = \frac{TP}{(TP + FN)} \quad (30)$$

5) FAR

It is crucial to select the performance criteria that are used to assess machine learning and deep learning techniques.

$$FAR = \frac{FP\_BENIGN}{TN\_BENIGN + FP\_BENIGN} \quad (31)$$

When benign data is mistakenly categorised as benign, it is indicated as True Negative (TN).False Positive denotes innocuous data that has been misclassified.

B. Performance Analysis

Fig 3 to 8 portrays simulation results of AEAM-VONN method. Then, the proposed method is AEAM-VONN likened with existing NDLM-EIPD-APSO, STEP-AGAI-DNN and PDA-PDO methods.

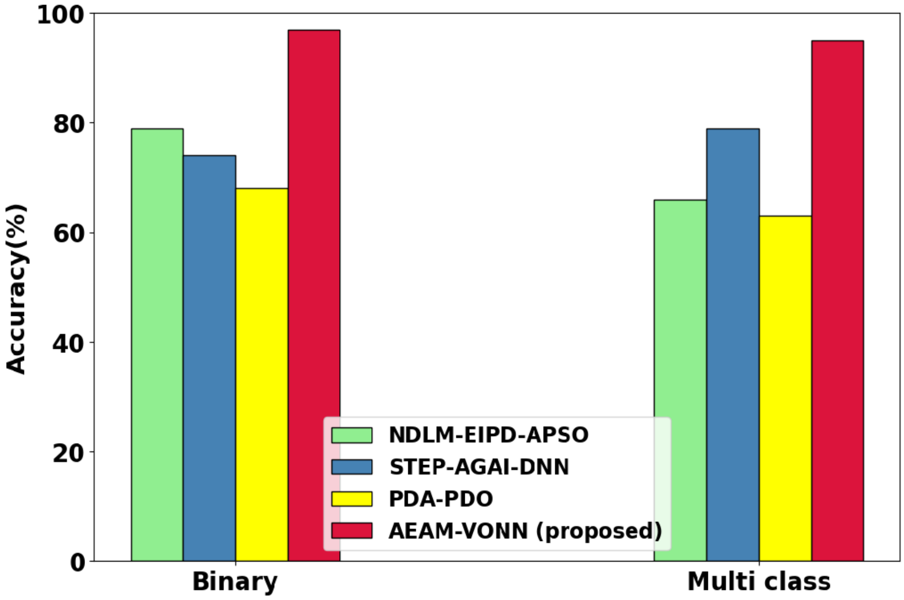

Fig 3: Performance Analysis of Accuracy

Fig 3 represents the accuracy analysis. The proposed AEAM-VONN binary provides the accuracy of 89.80% compared to the existing and Multi class proposed attains the accuracy of 78%. Existing method 30%,60%,65% in binary and 65%,55%60% in multi class. When evaluated to the existing NDLM-EIPD-APSO, STEP-AGAI-DNN and PDA-PDO models.

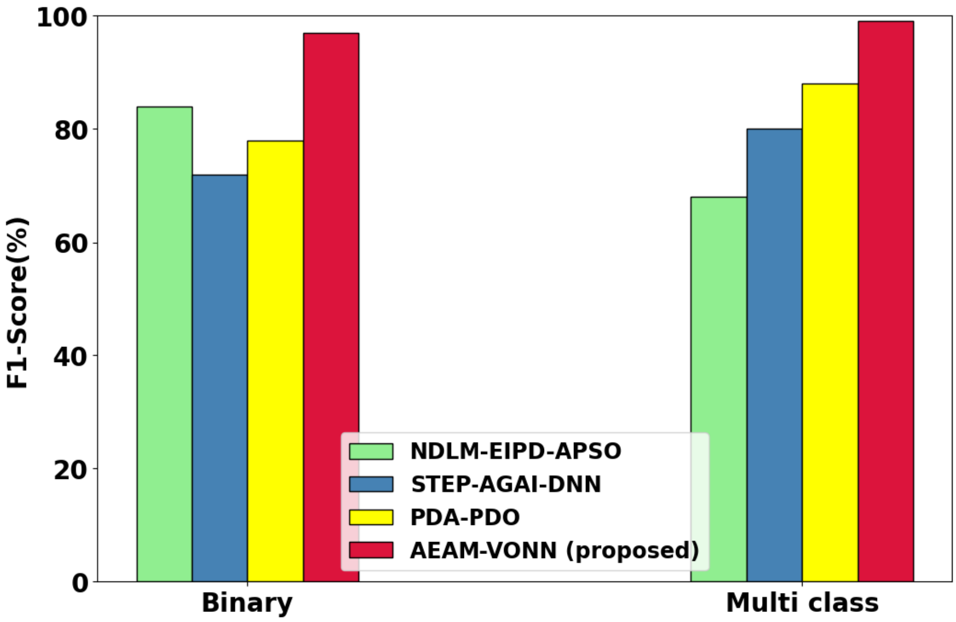

Fig 4: Performance Analysis of FI-Score

Fig 4 represents the FI-Score. The proposed AEAM-VONN binary provides the FI-Score of 59.89% compared to the existing and Multi class proposed attains the FI-Score of 69.99%.Existing method 60%,50%,35% in binary and 55%,45%,62% in multi class. When evaluated to the existing NDLM-EIPD-APSO, STEP-AGAI-DNN and PDA-PDO models respectively.

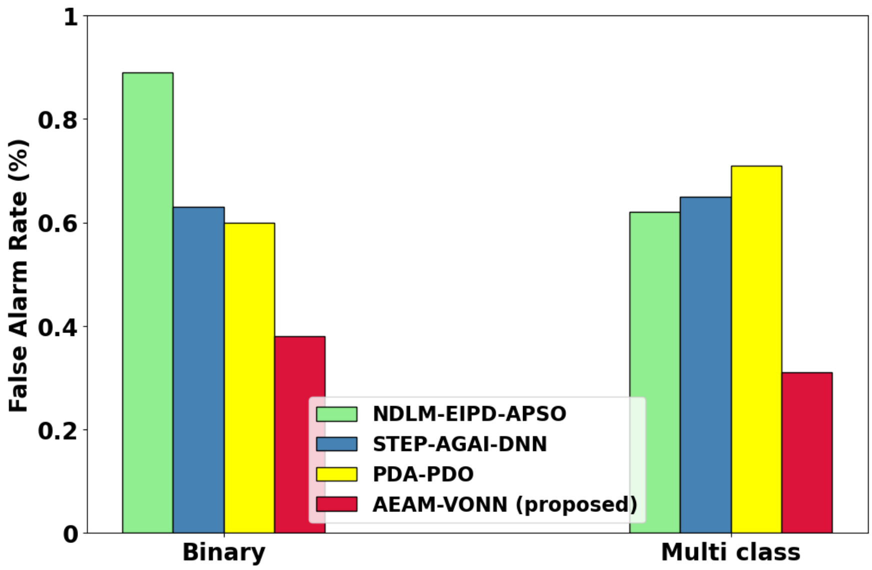

Fig 5:Performance Analysis of False Alarm rate (FAR)

Fig 5 represents the FAR. The proposed AEAM-VONN binary provides the FAR of 03.99% is higher when compared to the existing and Multi class proposed attains the FAR of03.93%.Existing method 0.9%, 0.6%, 0.6% in binary and 0.6%, 0.07%, 0.07% in multi class. When evaluated to the existing NDLM-EIPD-APSO, STEP-AGAI-DNN and PDA-PDO models respectively.

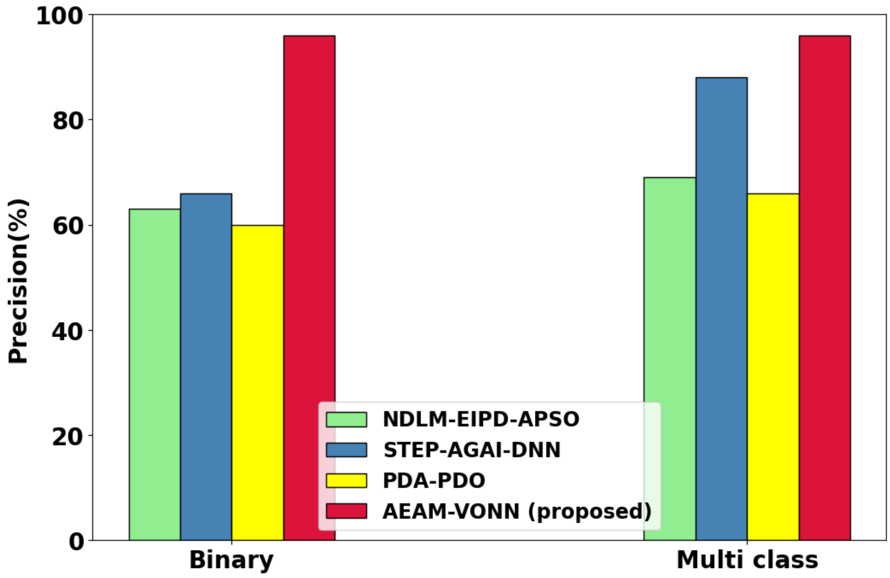

Fig 6: Performance Analyses of Precision

Fig 6 represents the Precision. The proposed AEAM-VONN binary provides the precision of 68.90% is higher when compared to the existing and Multi class proposed attains the precision of 88.90%.Existing method 50%,564%,59% in binary and 34%,40%,50% in multi class. When evaluated to the existing NDLM-EIPD-APSO, STEP-AGAI-DNN and PDA-PDO models respectively.

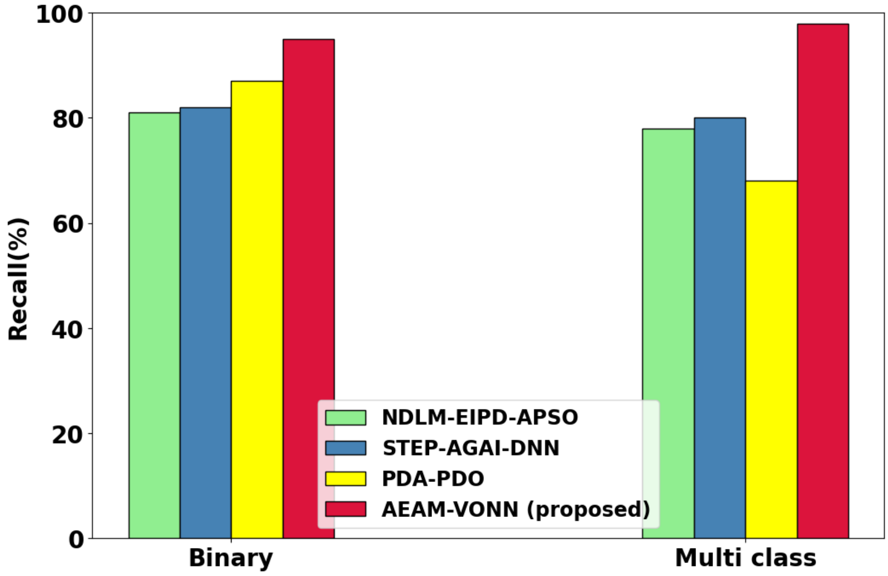

Fig 7: Performance Analyses of Recall

Fig 7 represents the Recall. The proposed AEAM-VONN binary provides the recall of 73.93% is higher when compared to the existing and Multi class proposed attains the recall of 72.90%.Existing method 50%, 62%, 45% in binary and 35%, 62%, 79% in multi class .When evaluated to the existing NDLM-EIPD-APSO, STEP-AGAI-DNN and PDA-PDO models respectively.

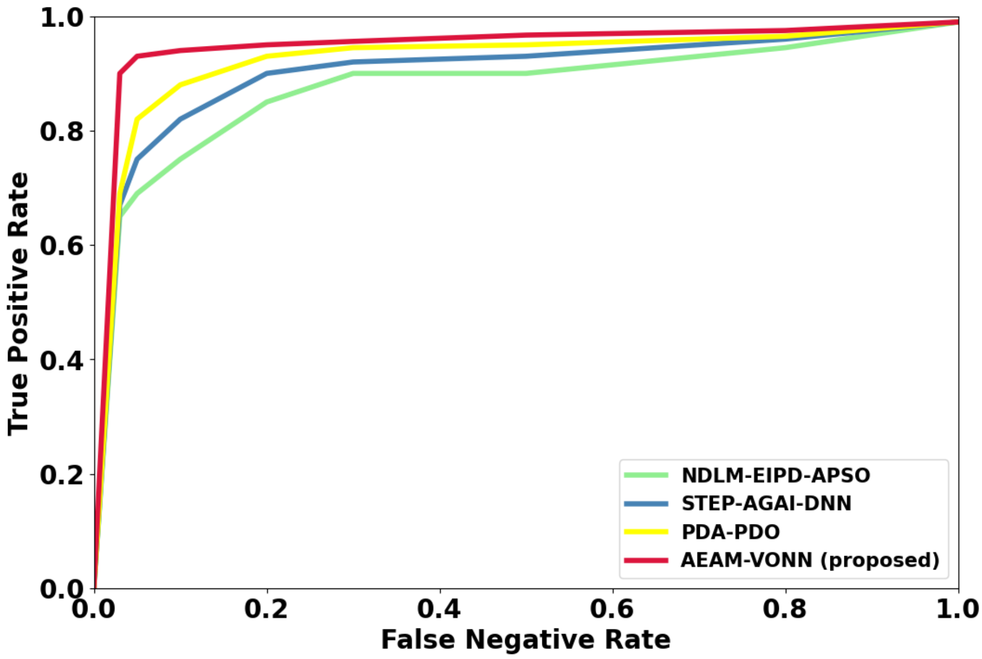

Fig 8: ROC curve for multilabel classification

ROC curve for multilabel classification is displayed in Figure 8. The score, which functions as a gauge for overall effectiveness. Score of 100%, demonstrating its continued dominance in identifying incursions. The elevated AUC value suggests that RF demonstrates a low false positive rate combined with a high true positive rate, making it the perfect option for detecting intrusions in WSNs.

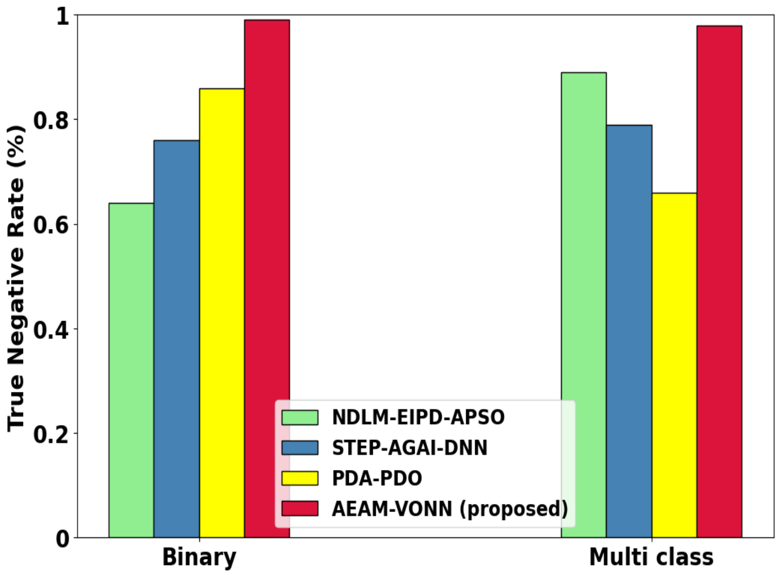

Fig 9: Performance Analysis of True Negative Rate

Fig 9 represents the True Negative Rate. The proposed AEAM-VONN binary provides the True Negative Rate of 75.80% is higher when compared to the existing and Multi class proposed attains the True Negative Rate of 76.95%.Existing method is 0.07%, 0.07%, 0.8% in binary and 0.8%, 0.7%, 0.6% in multi class. When evaluated to the existing NDLM-EIPD-APSO, STEP-AGAI-DNN and PDA-PDO models respectively.

C. Discussion

An AEAM-VONN model for a questionnaire and focus group discussion guide based on survey data is developed in this paper. The AEAM-VONN method involves encompasses based data pre-processing. Instance of questionnaire and focus group discussion guide based on survey data, the average highest outcomes of the approach were compared to the average results given in existing methods like NDLM-EIPD-APSO, STEP-AGAI-DNN and PDA-PDO respectively. The accuracy values of NDLM-EIPD-APSO, STEP-AGAI-DNN and PDA-PDO are 77.5%, 62.6% and 75.4% respectively, lesser than proposed method. Similar to this, whereas the average specificity value of comparison techniques is 83.44%, the specificity value of the suggested method is 98.93%.The proposed method AEAM-VONN has high and accuracy evaluation metrics than existing methods. Therefore, the comparative techniques are economically more expensive than the proposed method. It effectively addresses the challenges associated with the socialized teaching and demonstrates superior performance compared to existing methods.

V. CONCLUSION

In conclusion, this paper proposes Construction and Application of Agricultural Economic Audit Model Based on Big Data Analysis. The Unsharp Structure Guided Filtering is used to eliminate the missing data during pre-processing. The pre-processing result is forwarded to the CKFM is to efficiently classifies the credibility levels of highly credible, fairly credible and not credible. The proposed AEAM-VONN approach is implemented in Python utilization of questionnaire and focus group discussion guide based on survey data. Various scenarios are examined for the suggested method, including recollection, calculation time, sensitivity, specificity, accuracy, and precision. Presentation of proposed CTDP-MMIM-DCGNN method covers 30.56%, 21.76%, 35.97% higher specificity for highly credible; and 29.47%, 38.76% and 28.78% lower computational time for highly credible analyzed to the existing methods such as like NDLM-EIPD-APSO, STEP-AGAI-DNN and PDA-PDO respectively.

Acknowledgement

1. Youth Fund Project of Xinyang Agricultural and Forestry University in 2019: Research on Agricultural Informatization Construction in Henan Province under the Background of "Rural Revitalization Strategy" ,Project No.: 2019RW005.
2. Youth Fund Project of Xinyang Agricultural and Forestry University in 2020: Research on Environmental Audit Path Optimization for the Construction of Ecological Civilization , Project No.: 20200206.

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