Journal of Namibian Studies, 35 (2023): 2382-2409 ISSN: 2197 - 5523 (online)

A Hybrid Machine Learning based Audit classification: A Meta-Heuristic Approach

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paper received 08/05/2023, paper published 09/2023

Abstract

Audit classification is the process of classifying audits according to their type, goal, or focus areas. In order to manage and report audit activities effectively, it entails classifying audits into various types or categories. The classification facilitates better planning and resource allocation by assisting stakeholders, management, and auditors in comprehending the goals and scope of each audit. The raw audit data is cleaned during the pre-processing stage to remove noise and inconsistencies, and then min-max normalisation and standardisation is applied to ensure robustness and comparability of the data. In order to gather pertinent information and characterise the audit data, the feature extraction step makes use of “statistical measures”. From the extracted data, features are selected through New Hybrid Optimization named- RCSO using Sand Cat Swarm Optimization (SCSO) and Artificial Rabbit Optimization (ARO). From the selected features, classification is processed using Support Vector Machine (SVM) and Optimized Artificial neural networks (ANN). The proposed model is implemented using MATLAB programming. The proposed model can be guaranteed to be a more effective technique than the existing technique in terms of performance metrics because the model's execution is compared to existing technology. The proposed method's performance is compared to that of already-in-use methods like ANN, SVM, KNN, and Naive Bayes. The analysis of the model under consideration includes consideration of its sensitivity, recall, MCC, precision, specificity, F-score, FNR, FPR, NPV, and accuracy.

Keyword: *Auditing, Optimized ANN, Artificial Rabbit Optimization, Sand Cat Swarm Optimization.*

Nomenclature

Abbreviation	Description
ANN	Artificial neural networks
ARO	Artificial Rabbit Optimization
CAATs	Computer-Assisted Audit Techniques
IQR	Interquartile Range
IT	Information Technology
ML	Machine Learning
MRA	Model Risk Audit
NNs	Neural Networks
RCSO	Rabbit Customized Swarm Optimization Algorithm
SAI	Supreme Audit Institutions
SCSO	Sand Cat Swarm Optimization
SD	Standard Deviation
SVM	Support Vector Machine

1. Introduction

In recent years, IT Information Technology [1] has become widely used in the global business environment. This is largely due to the unexpected shifts in customer needs and the pressure to get the message rivals by offering timely, more top-notch services at lower amounts. Given that auditing is a laborious career, it is fundamental to consistently emphasise proficiency and competitivity to expand auditor efficiency overall the auditing process. In order to improve effectiveness, promote faster communication, and ascertain the assurance of customer detail, IT should be utilized throughout the auditing action [2]. The recent implementation of audit tendering rules increases the pressure on audit firms to improve their efficiency and prepare for possible price competition [3]. The word "auditing" originates with the Latin verb "audire," which suggests "to hear"; in the previous, auditors would take heed to officers and other figures of command in order to prove the truthfulness of their claims. The intention of accounting has transformed gradually to comprehend confirming scripted reports, specifically the economic records of individuals and enterprise [4,5]. Since its inception, audit has drawn a lot of attention and been defined in a variety of ways, including check, control, review, inspect, and examine. In most of the ancient civilised world, including Rome, Greece, China, and Egypt, clerks were chosen to monitor and check the goods of the merchants. Over the years, auditing has evolved from a traditional system to a modernised audit system [6,7].

The integrity and credibility of financial reports are crucial for efficient- operational markets, and the financial production of companies can be improved with an objective quality audit. It perform an necessary function in holding the "financial performance" of the enterprise [8]. External audits conducted in accordance with supremacy auditing beliefs can reinforce how relevant entities apply accounting principles and help to ensure that their economic reports are helpful, obvious, and trustworthy. An unrelated audit would help companies strengthen their internal controls, risk management, and corporate governance standards, which would improve their financial performance [9,10].

ML selects the particular algorithm based on the mission [11]. The pre-processed data set is then split into a training set and a test set, with the training set is used to teach the model. In the meantime, it determines the model's best function expression by calculating the loss function. It evaluates how well the best function generalises to the test set. This self-learning feature of ML allows computing machine take professional judgement that is somewhat comparable to that of humans, removing the restriction placed on the analysis process by its reliance on subjective incident [12]. A full population auditing method based on ML can find abnormal samples very quickly. In particular, it gives the machine the ability to learn the financial staff's accounting rules, which significantly boosts audit efficiency. Machines can examine a greater number of samples with a great deal more efficiency than humans can. This method is useful for identifying discrepancies in the accepted accounting principles as well as for checking human error in the workplace. This method, in particular, can assist large-scale businesses in locating tiny error swiftly and obtaining more comprehensive audit prove at a reduced audit costs [13].

The following is a list of the contribution of the suggested research work:

- To select Optimal Feature using New Optimization Algorithm RCSO.
- To introduce a new Hybrid ML model by combining SVM & Optimized ANN.
- To Fine Tune the weight of ANN using the new Hybrid Optimization - RCSO.

The following portion of the paper is carried out as follows: The work is divided into four 5 main sections. The paper examines previously completed work in its second section. Section 3 provides a description of the proposed audit classification plan. A comprehensive discussion of the outcomes obtained with the proposed model is provided in Section 4. The conclusion is found in 5th section.

2. Literature Review

In 2017, Appelbaum *et al.* [14] have proposed audit analytics and Big Data should be adopted by the external audit profession. Following that, it discussed the laws governing audit evidence and investigative techniques in comparison to the nascent Big Data and advanced analytics industries. The audit profession have the ability to engage in more complex predictive and “prescriptive-oriented analytics” in a Big Data environment. Also, focused on the research necessities of quantification of assessment and reporting, proposed and discussed half dozen key research questions and concepts.

In 2012, Mohamed *et al.* [15] have focused on both “internal audit competency” and internal audit's dues to financial statement audit and audit fees. This research was special in that it used information from three different sources, including annual reports, responses from internal and outside auditors, and information that was made available to the public. The overall findings of the research support the alternative perspective by showing a negative correlation between both IA quality aspects and audit fees.

In 2020, Manita *et al.* [16] have demonstrated how digital technology was affecting audit firms, particularly the audit role as a governance agency, at five key levels. Audits would become more relevant as a result of digitization, enabling audit firms to expand their service offerings. The audit quality would also be raised, primarily through customer analysis of all data. Finally, the digitalization has led to the appearance of a new auditor form, which has facilitated the culture of innovation interior audit firms. As a result, the management team's discretionary power would be constrained while the firm governance would be improved.

In 2019, Bonollo *et al.* [17] have offered suggestions for how to evaluate the results of SAI audits. The author offers valuable guidance on how SAIs could enhance the outcomes of their audits, most notably the importance of establishing follow-up routines to track the results of their audit suggestions. The research outlines suggestions that public auditors could use to obtain a thorough understanding of end result measures to enhance accountability.

IN 2023, Munz *et al.* [18] have suggested bridging this gap by utilising anticipatory opinion and a yielding “MRA” framework, which would allow organisations to benefit from ethical AI. With the help of this strategy, businesses could characterise risk at the model level and implement the proactive planning techniques used by high reliability organisations to deploy AI responsibly.

In 2021, Anh *et al.* [19] have analysed data that was gathered in Vietnam, also adds to the body of knowledge about how perceptions of digital transformation affect audit quality. It indicates that alterations in audit users' perceptions, changes in regulations, variations in auditors' work, and changes in auditors' specialist profiles all have a significantly positive relationship with audit worth in the net era. The findings contributed to the body of knowledge on audit quality while also enhancing the necessary alter in an audit by incorporating novel approach in the context of Vietnam.

In 2020, Ucoglu *et al.* [20] have proposed content analysis that was used to look at the ML platforms and tools created by the Big Four companies. It has been established that the Big Four companies created a number of ML tools used for stable audit teamwork and management, fully automated audits (only in specific areas, such as cash audits), data analysis, assessing the threat, and information extraction from archive.

In 2020, Serpeninova *et al.* [21] have discussed the key issues surrounding the classification of IT in auditing and the use of CAATs by auditors during the organisation of the audit process. The authors emphasise that the adoption of CAATs varied by firm size as one of these issues. The size of the auditing firm and the rate of technological advancement are directly correlated. Generalised CAATs and IT types include audit software, electronic spreadsheets, and electronic working papers. In addition to these technologies, auditors can frequently access and modify data using a programming language. Utility software and specialised audit software are frequently used to carry out particular auditor tasks or make it easier to complete a number of audit functions.

In 2020, Akman *et al.* [22] have determined the best auditing procedures for preventing cost accounting frauds. In this research, the case analysis method was used to examine the best auditing practises for identifying and preventing fraud. As part of the case analysis, the well-known scandals involving the companies Olympus, Worldcom, Tesco, Sunbeam, and Parmalat were also examined. Finally, fraud prevention strategies was suggested and offered as recommendations.

2.1. Research Gaps

In the modern era, technology is incorporated into the recording process. The practice still relies on manual checkups and disregards inward controls based on the certain technology employee of the business. Despite the dissimilarity in technology poses a problem, this audit system does not cover any safeguards versus such challenges. The reporting hide all information about the figures and data used in the evaluation. Therefore, report does not assure any defences.

3. Proposed Methodology

Machine learning algorithms are used to sort audit-related tasks and data into various classes. This process is known as audit classification. This method can be especially useful for automating the classification of sizable amounts of audit-related data, lowering manual labour requirements, and enhancing efficiency and accuracy. The proposed model includes some major phases: Initially: Pre-processing then Feature extraction, Feature Fusion, feature selection, to sum up with classification. Figure 1 shows overall architecture of the proposed methodology.

- **Pre-processing**: Data cleaning, min-max normalization and standardization are used for pre-process the audit data. The process of locating and fixing mistakes, inconsistencies, and inaccuracies in the audit dataset is known as data cleaning. Cleaning the data is important for a reliable analysis because audit data can come from different sources and may be subject to human or data entry errors.
- **Feature Extraction:** In order to summaries the distribution of the raw data and derive useful features, statistical feature extraction involves computing various statistical metrics from the raw data. Statistical features like (mean, median, standard deviation, skewness, kurtosis, variance, moment, IQR) are used for feature extraction.
- **Feature selection:** Sand Cat Swarm Optimization and Artificial Rabbits Optimization are combined as a Hybrid optimization.
- **Audit classification**: SVM and optimized ANN (hidden layers and neurons of ANN optimized via hybrid optimization algorithm) are the final process. SVM and an optimized Artificial Neural Network (ANN) are combined in the classification process's final step to produce a more potent and precise classification model. The hybrid optimization algorithm is used to enhance the model's overall performance by optimizing the ANN's architecture, particularly the number of hidden layers and neurons.

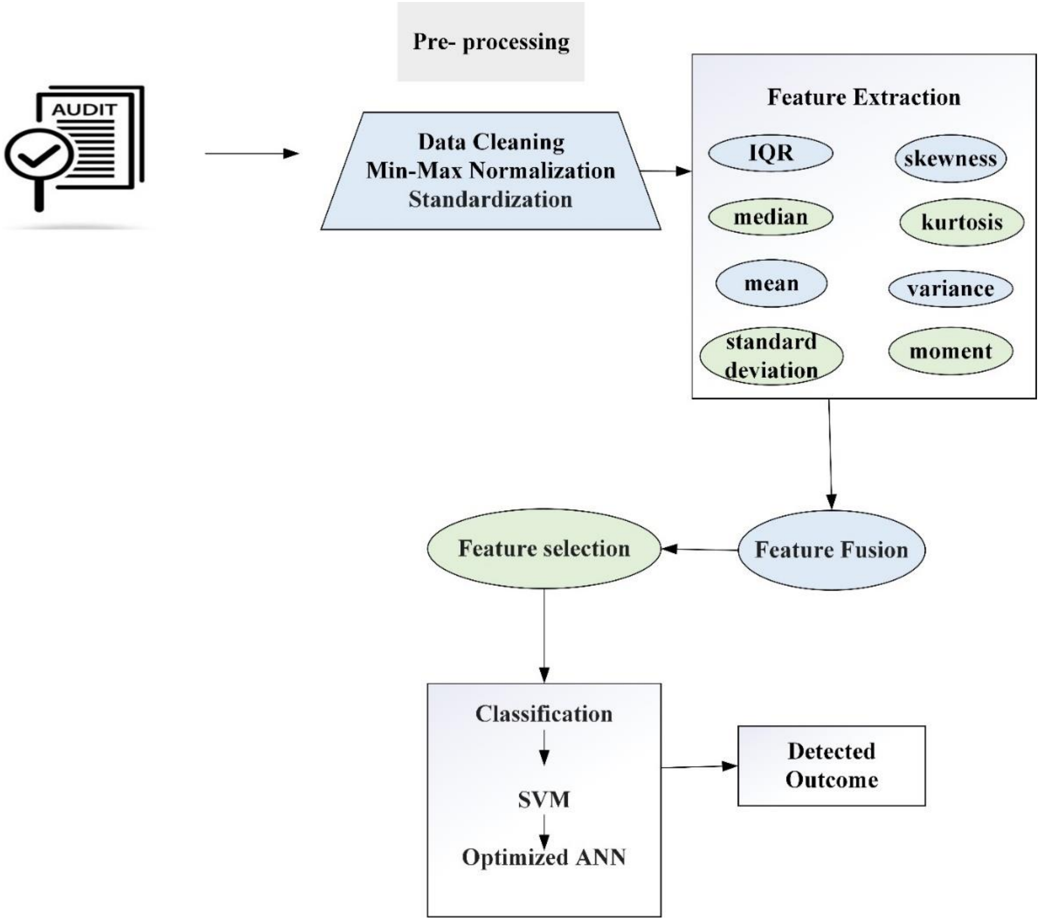

Figure 1: Overall proposed flow

3.1. Pre-processing

Effective pre-processing in audit classification helps to improve the data's quality, enhance feature representation, and address class imbalance, producing classification results that are more accurate and dependable. In this research work, Pre-processing is processed using for the collected data through Data Cleaning, Min-Max Normalization, and Standardization. Figure 2 shows the graphical explanation of Pre-processing.

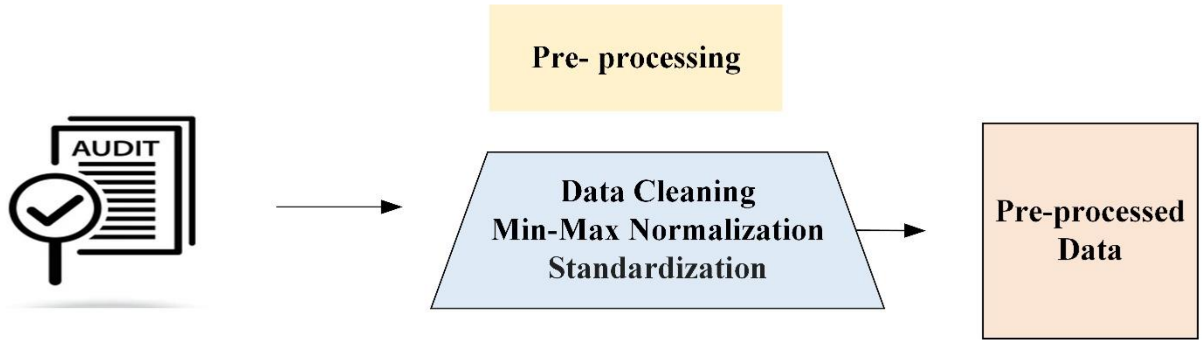

Figure 2: Pre-processing Stage

3. 1. 1. “Data cleaning”

Low-grade data may have a negative impact on organisational effectiveness and ability as data is used progressively to encourage organisational activities and guide business decisions. Bulk organisations' top concern is the peculiarity of their data. Indeed, this problem is the result of broken-down, which also causes contradiction in the database. One of the challenges to effectively using the data is data worth because poor data can result in erroneous decisions. It can offer a spectrum of benefits to the organisation, but only with excellent data are they able to release the enhanced services possible. Analysing the data to find errors and inconsistencies in the database is known as data cleansing. In other words, this stage is known as data auditing, and it is during this stage that all kinds of anomalies within the database is discovered.

3. 1. 2. Min-Max Normalization

The simplest and most reliable method for rescaling is also referred to as min-max scaling. Features that can be scaled in $[0,1]$ or $[1,-1]$. The result is smaller standard deviations, which can mitigate the impact of outliers. Conditional on the data's nature, the target range must be elected. The Eq. (1) is the overall formula for a “min-max” of $[0,1]$.

$$a' = \frac{a-min(a)}{max(a)-min(a)} \tag{1}$$

a' stands for the normalised score of a.

3. 1. 3. Standardization

Standardisation, also known as the z-score. Standardisation is crucial because it enables dependable data transmission between different systems. The communication and data exchange between computers would be facilitated by standardisation. A database's processing, analysis, and storage processes are also made easier by standardisation. With this approach, businesses can use their data to inform better decisions. When data is standardised, businesses can more easily compare and evaluate it, giving them insights into how to run their businesses better.

Audit data is processed into a cleaner, normalised, and standardised format by implementing data cleaning, min-max normalisation, and standardisation. These pre-processing steps enhance the data's quality, boost the effectiveness of machine learning models, and make the data better suited for various statistical analyses. In the end, these actions help to improve the classification and analysis of audit data.

3. 2. Feature Extraction

In this research work, the pre-processed data are fed up into feature extraction. Feature extraction is done using Statistical Features like. Figure 3 shows Feature extraction phase.

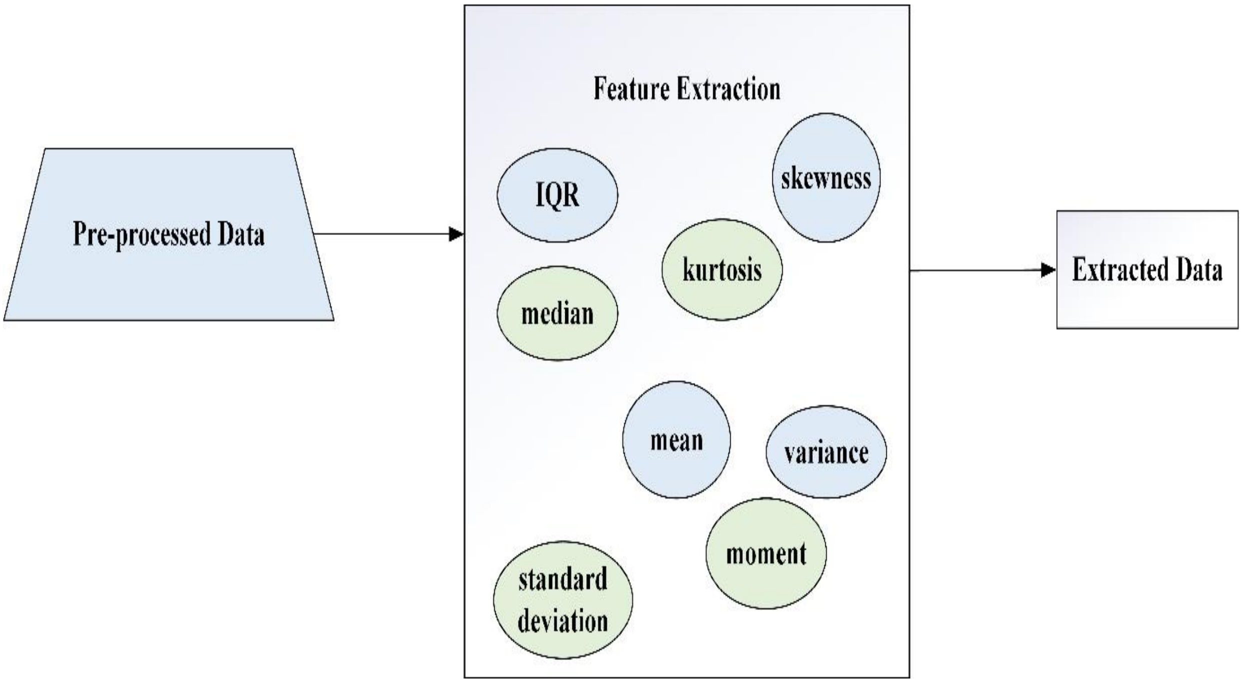

Figure 3: Phase of Feature Extraction.

3. 2. 1. Statistical Features

The characteristics of a dataset that can be identified and calculated through statistical analysis are known as statistical features. It is the statistical concept that data science probably uses the most.

3. 2. 1. 1. Mean

The average value of a group of data points is known as the mean. It gives an indication of the data's central tendency and represents the typical value around which the data points tend to congregate. The mean can be used to determine the average value of particular financial metrics in the context of audit data, offering helpful insights into overall financial performance. The sum of a various numbers divided by the overall amount of the accumulation is known as the arithmetical mean, also known as the “mean or average”. The mathematical expression is shown in Eq. (2).

$$Mean(\bar{b}) = \frac{b}{A} \tag{2}$$

3. 2. 1. 2. Median

The middle value in a sorted set of data points is known as the median. It offers an alternative measure of central tendency and is resistant to outliers. The median in audit data can be used to evaluate the typical value of financial indicators while taking into account the existence of extreme values or anomalies. The median, which is the middle number in a list of numbers is sorted either exponentially or descending, might a better hand of the data set than the normal. The mathematical expression is shown in Eq. (3) & Eq. (4).

$$Median = \left(\frac{n+1}{2}\right)^{th} \text{observation} \tag{3}$$

The following formula is used if the data set contains an even number of terms:

$$Median = \frac{\left(\frac{n}{2}\right)^{th} observation + \left(\frac{n+1}{2}\right)^{th} observation}{2} \tag{4}$$

3. 2. 1. 3. SD

The variability or dispersion of data points around the mean is measured by the standard deviation. It measures how much the mean is deviated from by each individual data point. The standard deviation can be used in audit data analysis to comprehend the range or volatility of financial metrics, such as revenue or expenses. The standard deviation, which is expressed as a numerical value, describes how measurements for a group differ from the mean or expected value. A low standard deviation indicates that most of the numbers are within a few standard deviations of the average, whereas a high standard deviation indicates that the numbers are more dispersed. SD is a calculation of how much a set of values vary or are scattered. The mathematical expression is shown in Eq. (5).

$$Standard\ Deviation = \sqrt{\frac{\sum(b_i - \mu)^2}{A}} \tag{5}$$

3. 2. 1. 4. Skewness

The level of asymmetry present in a probability distribution is known as skewness. Different degrees of right (positive) or left (negative) skewness can be seen in distributions. Zero skewness is present in a bell-shaped distribution, which is normal. Investors take right-skewness into consideration when assessing a return distribution because it more accurately captures the extremes of the data set than if they only looked at the average. Although it does not reveal the frequency, skewness informs users of the direction of outliers. Stock market returns and the distribution of average individual income both frequently exhibit skewness. It is a statistical measure used to ascertain how a distribution is even or not. If the right path of the distribution resembles the left side, the distribution is said to be symmetrical. A distribution's skewness value is zero if it is symmetric. Right-skewed data applies to data in which the right tail is longer than the left tail and Skewness is greater than zero. Left-skewed or having a longer left tail than right is the result if Skewness is less than 0. Audit data skewness may reveal financial metric imbalances, pointing to potential problems or areas of concern. The Eq. (6) defines skewness (γ_1)

$$(\gamma_1) = A\left[\left(\frac{b - \bar{b}}{\sigma}\right)^3\right]$$
$$= \frac{\mu_3}{\sigma^3} \qquad (6)$$

3. 2. 1. 5. Kurtosis

If a distribution is extended or briefer than a normal distribution, it can be determined using a statistical measure called kurtosis. If a distribution imitates the "normal distribution", the Kurtosis value is zero. If kurtosis is higher than 0, it has a superior peak than the normal distribution. If kurtosis > 0, the distribution is flatter than a normal distribution. Kurtosis can shed light on the shape of the distribution in audit data, which may have implications for forecasting or risk assessment. The fourth standardized moment, kurtosis (β_2) is described in Eq. (7).

$$\beta_2 = A\left[\left(\frac{b\_\bar{b}}{\sigma}\right)^4\right]$$
$$= \frac{\mu_4}{\sigma^4} \qquad (7)$$

3. 2. 1. 6. Variance

Variance is the anticipated square deviation of a random variable from its mean. The variance is intentional by partition the sum of the squares of the deviations from the mean (μ) of all the terms in the distribution by the certain words (A). Variance in audit data can be used to gauge how variable financial performance indicators are. The mathematical expression is shown in Eq. (8).

$$Variance(\sigma^2) = \frac{\sum(b_i - \mu)^2}{A} \qquad (8)$$

3. 2. 1. 7. Moment

The Euclidean separation between the boundary points (A_u, A_c) and centroid (Q_a, Q_j) is the order sequence $S(\text{Four})$. Fourier is index of Fourier descriptors and u represents the total number of boundary coefficients. Eq. (9) - Eq. (11) can be used to calculate the moments of the second order central sequence $\mu_2$and the second order contour sequence n_2.

$$n_1 = \frac{1}{\text{Four}} \sum_{\text{Four}=1}^{\text{Four}} \big(S(\text{Four})\big) \tag{9}$$

$$n_2 = \frac{1}{\text{Four}} \sum_{\text{Four}=1}^{\text{Four}} \big(S(\text{Four})\big)^2 \tag{10}$$

$$\mu_2 = \frac{1}{\text{Four}} \sum_{\text{Four}=1}^{\text{Four}} (S(\text{Four}) - n_2)^2 \tag{11}$$

3. 2. 1. 8. IQR

The interquartile range, which has a breakdown point of 25% unlike the total range, is frequently chosen over the total range. Box plots, which are straightforward graphical representations of a probability distribution, are created using the IQR. Businesses use the IQR as a gauge for their income rates. Half of the IQR corresponds to the median absolute deviation (MAD) for a symmetric distribution. The equivalent measurement of central tendency is the median. Outliers can be located using the IQR. The IQR might also show how skewed the dataset is. Half of the IQR is referred to as the quartile deviation or semi-interquartile range. A technique for identifying outliers in continuously distributed data is IQR. There is a disagreement among the first and third quartiles; the “IQR” is also known as the middle 50%, midspread, and formally the H-spread. The points of 25% can be divided using IQR to produce a boxplot, which is a simple graphical representation of IQR. The mathematical expression is shown in Eq. (12).

$$IQR = Q_3 - Q_1 \tag{12}$$

3.3. Feature Fusion

Feature Fusion is the combination into a single unified feature representation.

3.4. Feature selection

It is a significant step in the Classification. The proposed method for feature selection in this research work is a hybrid optimization model that is RCSO that combines SCSO and Artificial Rabbits Optimization. The RCSO method aims to find the most pertinent and instructive features for a given task in order to address the difficulties of feature selection in complex datasets. Figure 4 shows the phase of Feature selection

Figure 4: Feature Selection Phase.

3.4.1. SCSO

Simulations of sand cats foraging in the desert served as the foundation for the SCSO algorithm. The sand cat uses low frequency noise to find prey above or below ground. Through location updates, the search agent continuously explores the search space, eventually advancing towards the region where the optimal value is situated. The ideal value in the exploration space is treated as prey by the algorithm. The SCSO algorithm includes both a prey search mechanism and a prey attack mechanism. The method of hunting for prey can resemble sand cat behaviour.

3.4.2. ARO

ARO, a brand-new gradient-free meta-heuristic algorithm, will be released in 2022 and mimics rabbits' natural survival strategies. Rabbits are herbivores, so they mostly eat grass and weeds with leaves. Because doing so would draw predators to their own nests, rabbits avoided eating the grass around the holes and instead frequently looked for food elsewhere. This detour foraging strategy is known as exploration in ARO. Because they are adept at making a variety of holes for their nests before selecting one at random to serve as a shelter, rabbits are less likely to be preyed upon by hunters or other predators. This careless method of hiding is viewed as exploitation in ARO. Because they are lower on the food chain than other animals, rabbits must move quickly to stay safe from a variety of predators. They lose energy as a result, and in order to adapt, they must alternate between detour foraging and random hiding depending on their energy level. The details of rabbits' biological habits are used to construct the mathematical model of ARO, which includes exploration, the transition from exploration to exploitation, and exploitation.

3.4.3. RCSO

Step 1. Initialization

Each search agent is a $1 \times dim$ array in the dim dimension optimization dilemma. It stands for the issue's resolution. Each z must be contained within the lower and upper boundaries of a set of variable values $(z_1, z_2, \ldots\ldots, z_{dim})$. According to the size of the problem $(N * dim)$, the boot-up algorithm creates an initialization matrix. Each iteration is the output of corresponding solution. If the next output value is better, the current solution is abandoned. The iteration's solution won't be saved if a better one is not found in the following round.

ARO is a novel gradient-free meta-heuristic algorithm that imitates rabbits' innate survival skills. Rabbits are primarily herbivores, meaning they eat grass and weeds with leaves. Because eating the grass around the holes would draw predators' attention to their own nests, rabbits frequently look for food elsewhere. In ARO, this method of detour foraging is referred to as exploration. In order to reduce their vulnerability to being captured by hunters or other predators, rabbits are skilled at making a variety of holes for their nests before selecting one at random to use as a shelter. This haphazard hiding method is viewed as exploitation in ARO. Because they are lower on the food chain than other animals, rabbits must move quickly to stay safe from a variety of predators. They lose energy as a result, and in order to adapt, they must alternate between detour foraging and random hiding depending on their energy level.

$$\vec{z}_{i,k} = r.(ub_k - lb_k) + lb_k, k = 1,2, \dots, d \qquad (13)$$

ub is the upper limit ND lb is the lower limit. $\vec{z}_{i,k}$ indicates the location of the ith rabbit's jth dimension, and r is an orderly number that is also provided.

Step 2: Lens Opposition-Based solution Generation

Convex lens imaging is the fundamental tenet of lens opposition-based learning. By creating a reverse position based on the current coordinated, the search area is widened. In 2D coordinates, the search range of the absciss is (a, b) and the vertical direction depict a convex lens. Assume that target A's height is h and that its projection on the x-axis is x. Through lens imaging, the image on the other side is A^* , A^* is planned on the x-axis as x^*, and the elevation is h^*. Across the above analysis, determine the revoke projection x^* of x. The lens imaging principle can be used to determine x corresponding reverse point x^* by using o as the base point. The mathematical expression is shown in Eq. (14).

$$\frac{\frac{(a+b)}{2} - x}{x^* - (a+b)/2} = \frac{h}{h^*} \qquad (14)$$

Let $k = \frac{h}{h^*}$ in order to derive Eq. (15) from lens opposition-based learning.

$$x_j^* = \frac{a_j + b_j}{2} + \frac{a_j + b_j}{2k} - \frac{x_j}{k} \qquad (15)$$

x_j is the individual’s site in the jth dimension and x_j^* is the inverse solution of x_j. a_j and b_j are the maximum and littlest boundaries of dimension j in the search space.

Step 3. Fitness Computation

A key idea in evolutionary algorithms and genetic programming is fitness computation. It describes the procedure of assessing the effectiveness or quality of individual solutions within a population in light of a particular fitness function. The fitness function is problem-specific and frequently entails assessing the problem's objective(s). Assessing an individual's performance in relation to the objectives or constraints of the problem is a common step in the evaluation of fitness. Simulation, mathematical calculations, or comparison with existing optimal solutions might all be necessary. The evolutionary algorithm then uses the fitness values to direct the selection and reproduction processes, favouring individuals with higher fitness for more research and potential development. The mathematical expression is shown in Eq. (16).

$$Fit = \max(A) \tag{16}$$

A is the accuracy of the audit classification.

Step 4. Solution Updation

Populations pick to carry out the exploration level in the former stages of an optimisation algorithm and an exploitation phase in the central and late stages. The energy of the rabbits is used by ARO to create a finding scheme because it depletes over time, simulating the transition from "exploration to exploitation". The energy factor in the algorithm for artificial rabbits is defined in Eq. (17)- Eq. (25).

A) Compute every factor using $A(t) = 4.\left(1 - \frac{t}{T_{max}}\right).\ln\frac{1}{r}$ (17)

where r is a given random number and r is the random number in $(0, 1)$.

B) If $A > 1$ then perform proposed sensitivity-based Detour foraging strategy.

Each rabbit's propensity to move away from the food source and investigate a different rabbit scene randomly selected within the group is known as detour foraging.

$$\vec{v}_i(t+1) = \vec{z}_j(t) + R.\left(\vec{z}_i(t) - \vec{z}_j(t)\right) + round\left(0.5.(0.05 + r_1)\right).n_1 \tag{18}$$

Where, $R = 2 * r_G * rand(0,1) - r_G$

r_G is the sensitivity. $\vec{z}_j(t)$ is the spot of j th dimension of the ith rabbit. $\vec{v}_i(t+1)$ represent recent spot of the search agent.

$$c(k) = \begin{cases} 1, if\ k == w(x) \\ 0, otherwise \end{cases} \quad lk = 1, \dots, G\ and\ x = 1, \dots., \lceil rand_3 * G \rceil \tag{19}$$

$$w = randperm(G) \tag{20}$$

$$n_1 \sim N(0,1) \tag{21}$$

$$\vec{z}_i(t+1) = \begin{cases} \vec{z}_j(t)\ if\ f\left(\vec{z}_j(t)\right) \leq f\left(\vec{v}_i(t+1)\right) \\ \vec{v}_i(t+1)\ else\ f\left(\vec{z}_j(t)\right) > f\left(\vec{v}_i(t+1)\right) \end{cases} \quad (22)$$

C) If $A \leq 1$, then perform Triangular walk based random hiding strategy (proposed).

The Eq. (23) allows the random hidden phase based on the Lévy flight, α is a parameter adhere to 0.1.

$$\vec{v}_i(t+1) = \vec{z}_j(t) + R.\left(\alpha\,.\,P.\vec{b}_{i,r}(t) - \vec{z}_j(t)\right), i = 1, \ldots, N \quad (23)$$

$$z + R.(\alpha.P.b - z) \quad (24)$$

Where, $P = L_1^2 + L_2^2 - 2 * L_1 * L_2 * cos(\beta)$ (25)

Step 5. Save the so far acquired best solution

Step 6. Terminate.

3. 5. Classification

In this research work, Classification is processed using SVM and an Optimized ANN. The SVM and an optimised ANN are used in this situation to perform classification. Both algorithms have their uses in classification tasks, but they each have their own advantages and limitations. Figure 5 shows the classification phase.

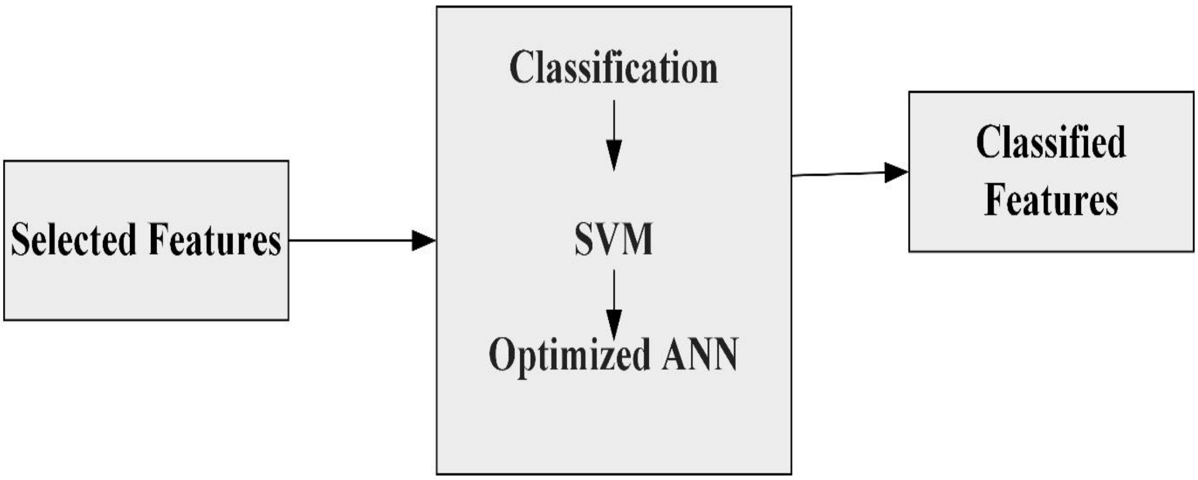

Figure 5: Classification Phase.

3. 5. 1. SVM

One of the most well-liked supervised learning algorithms, Support Vector Machine, or SVM, is used to solve Classification and Regression problems. However, it is primarily employed in Machine Learning Classification issues. The SVM algorithm's objective is to establish the best line or decision boundary that can divide n-dimensional space into classes, allowing us to quickly classify new data points in the future. A hyperplane is the name given to this optimal decision boundary.

Support vector machines' benefits include:

- Efficient in high-dimensional environments.
- Still useful in situations where the number of dimensions exceeds the number of samples.
- It is also memory effective because it only uses a portion of the training points in the decision function.
- Different Kernel functions can be specified for the decision function, making it versatile. There are common kernels available, but you can also specify your own kernels.

Finding a separating hyper-plane that can divide the dataset $(c_d, d = 1,2, \dots N)$ into two categories $(e_d = \pm 1)$ with the maximum margin is the goal of the SVM for binary classification. $+$ stands for data points in the class $+1$, and $-$ for data points in the class-1. Support vectors are the data points that were used to create the separating hyper-plane. Eq. 26 is used for calculating the parameters of the separating hyper-plane, (ω, f).

$$(\omega, f) \in \arg\ min \frac{1}{2} \|\omega\|_2^2 + B \sum_{n=1}^{N} D_{\omega,f}(c_d, e_d) \qquad (26)$$

Where, N-dimensional vector is ω and a scalar is f, Regularization parameter is B which modifies the trade-off between dataset sparsity and misclassification rate. $D_{\omega,f}(c_d, e_d)$ the hinge loss function, which is equal to max $\{0,0,1 - e_d(\omega^C c_d + f)\}$.

3. 5. 2. Optimized ANN

The biological neural networks that shape the structure of the human brain are where the term "artificial neural network" originates. Artificial neural networks also have neurons that are interconnected to one another in different layers of the networks, much like the human brain, which has neurons that are interconnected to one another. Nodes are the name for these neurons. ANN were used to categorise texture features. Numerous researchers have made extensive use of this methodology to describe the classification. The neurons that make up NNs are naturally occurring neurons. These neurons are linked to one another by particular links with weights that have been multiplied by the network's transmitted signals. The sigmoid activation function controls each neuron's output. NNs are trained using prior knowledge to forecast outcomes for unknowable inputs. The Eq. (27) determine the output.

$$g(h+1) = j\left(\sum_{l=1}^{k} E_F m_l(h) - \theta_o\right) \tag{27}$$

And $p_{o=\Delta net_o = \sum_{l=1}^{k} E_F m_l - \theta_o}$

Here, $m = (m_1, m_2, m_3, \ldots . m_k)$ displays the number of inputs that are applied to the neuron. θ_o is a bias value that the equation uses and $j(\,)$ Sigmoid function or activation function. The number of layers, activation function, sigmoid, and neurons within each layer must be carefully considered when designing a NN model. Used feed forward back propagation NN with hidden layers containing 37 neurons. A one-layer backpropagation network with the sigmoid activation function and four nodes makes up the ANN used in this system.

4. Result and Discussion

4.1. Dataset Description

The following are the study's three main goals: understanding the audit risk analysis work-flow of the business through in-depth interviews with audit staff, and recommending a framework for making decisions regarding risk assessment of businesses during audit planning. To evaluate the Risk Audit Class (Fraud and No-Fraud) of suggested firms and to rank the examined risk factors using the Particle Swarm Optimisation (PSO) algorithm after examining the current and historical risk factors for 777 target firms. The PSO algorithm will be used to rank the examined risk factors and determine the Risk Audit Score for 777 target firms. The Risk Audit Class (Fraud and No-Fraud) of the nominated firms will also be evaluated. The dataset is collected from Audit Classification [23].

4.2. Experimental Setup

The MATLAB programming is used to implement the suggested model. This section elaborates the graphical analysis for Audit classification. In this section, the performance metrics used for evaluating the performance of proposed model are discussed and it was compared with existing techniques.

4.2.1. Performance Metrics

i. Accuracy

The accuracy metric, which calculates the proportion of accurate predictions to all predictions, is one of the most straightforward Classification metrics to employ. The formula is mathematically expressed by Eq. (28).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{28}$$

ii. Precision

The percentage of false positives to all absolute cases is used to gauge precision. Precision formula is mathematically expressed by Eq. (29).

$$Precision = \frac{TP}{TP+FP} \tag{29}$$

iii. Sensitivity

Sensitivity is the likelihood of a positive test result, presuming the subject is in reality positive. The sensitivity formula is mathematically expressed by Eq. (30).

$$Sensitivity = \frac{TP}{TP+FN} \tag{30}$$

iv. Specificity

The ratio of accurately predicted negative outcomes over all negative outcomes is known as specificity. The formula for specificity is mathematically shown in Eq. (31).

$$Specificity = \frac{TN}{TN+FP} \tag{31}$$

v. F-Measure

The number strikes a balance between making sure that each definition explicitly only refers to one type of information item and fully determine each data bit. The formula for F-Measure is mathematically shown in Eq. (32).

$$F\_Score = \frac{Presision.Recall}{Presision+ Recall} \tag{32}$$

vi. Matthew's correlation coefficient (MCC)

The effectiveness of binary classification models is assessed using the MCC metric. MCC takes TP, TN, FN, and FP into account, making it a trustworthy metric for evaluating the effectiveness of binary classifiers. The level of correlation between the predictor and the actual labels is determined by MCC. The formula for MCC is mathematically shown in Eq. (33).

$$MCC = \frac{(TP*True\ Negative)-(FP*FN)}{\sqrt{(TP+FP)(TP+FN)(FP+TN)(TN+FN)}} \tag{33}$$

vii. NPV

A statistical measure known as NPV assesses the dependability of a negative test result in a population of people who have a particular condition. By dividing the total population that is free from the condition by the number of actual negative effects, it is done on purpose. The effectiveness of detection is evaluated using NPV. The formula for NPV is mathematically shown in Eq. (34).

$$\mathrm{NPV} = \frac{\mathrm{TN}}{\mathrm{TN+FN}} \tag{34}$$

viii. FPR

In order to determine the false positive rate, the entire number of bad case is divided by the number of adverse facts that were mistakenly classified as unfavorable. Eq. (35) provides a mathematical representation of the FPR formula.

$$False\ Positive\ Rate = \frac{FP}{FP+TN} \tag{35}$$

ix. FNR

It is also known as the "miss rate," is a measurement of the likelihood that a test would fail to discover a true positive. Eq. (36) presents the mathematical formula for FNR.

$$False\ Negative\ Rate = \frac{FN}{TP+FN} \tag{36}$$

4.2.2. Overall comparison of the proposed and Existing methodology

The performance of the proposed method is compared with the existing techniques like ANN, SVM, KNN & Naïve Bayes. The considered model is analysed and relating to Sensitivity, recall, MCC, precision, specificity, F- score, FNR, FPR, NPV and accuracy. Table 1 shows the proposed and Existing of performance metrics.

Table 1: Proposed Vs Exiting

	Sen	Spec	Acc	Precis	Recall	F-Measure	NPV	FPR	FNR	MCC
Proposed	0.968	1	0.980	1	0.968	0.983	0.95	0	0.031	0.95
ANN	1	0.931	0.974	0.960	1	0.979	1	0.068	0	0.945
SVM	0.948	1	0.967	1	0.948	0.973	0.920	0	0.051	0.934
KNN	0.907	0.896	0.903	0.93	0.907	0.921	0.852	0.103	0.092	0.796
Naïve Bayes	0.814	1	0.883	1	0.8144	0.897	0.763	0	0.185	0.788

The proposed algorithm maintains perfect specificity of 1 and reach a comprehensive accuracy of 0.980 & sensitivity of 0.968, indicating a high success rate. The accuracy of ANN is 0.974 despite its perfect sensitivity is 1 and slightly lower specificity of 0.931. Sensitivity of SVM is 0.948 and 1 for specificity. With an accuracy of 0.967, the SVM model achieves high sensitivity (0.948) and perfect specificity. With a sensitivity of 0.907 and a specificity of 0.896, the KNN algorithm performs admirably, yielding an accuracy of 0.903. The accuracy of the Naïve Bayes algorithm is 0.883 despite its low sensitivity of 0.814 and flawless specificity & 1 for specificity. The ANN and SVM models perform admirably, followed closely by Proposed, while the KNN algorithm performs merely passably and the Nave Bayes algorithm trails behind in terms of sensitivity. The proposed achieves a recall of 0.968, which means it correctly recognises 96.8% of positive instances, and precision, which shows that all positive predictions are correct. It achieves a high F-measure of 0.983, which shows a carefully considered trade-off between recall and precision. The F-measure for ANN is 0.979, with a precision of 0.960, correctly identifying 100% of positive instances (recall of 1). With a recall of 0.948 and an F-measure of 0.973, SVM achieves perfect precision, correctly identifying each and every instance of a positive response. The KNN algorithm performs well, with an F-measure of 0.921, a recall of 0.907, and a precision of 0.93, correctly identifying 90.7% of positive instances. The F-measure for Nave Bayes is 0.897 because it has perfect precision but a recall score of 0.8144. The proposed algorithm successfully detects negative instances with a high success rate, as evidenced by its high NPV of 0.95. It also has a low FNR, which is zero. The predicted and actual labels appear to be strongly correlated, according to the MCC of 0.95. The ANN model shows a perfect NPV of 1, correctly identifying all instances of failure. It has a low false positive rate (FPR) is 0.068 and zero FNR, indicating that it correctly identifies all positive instances. According to the proposed algorithm, the MCC of 0.945 indicates a strong correlation between the predicted and actual labels. The SVM model successfully and accurately detects negative events with an NPV of 0.920. It has a low false negative rate (FNR) of 0.051, indicating a low percentage of false negatives. The predicted and actual labels appear to be strongly correlated, according to the MCC of 0.934. KNN displays an NPV of 0.852, which shows a disproportionately high percentage of false negatives. It has a FNR of 0.092 and an FPR of 0.103, both of which point to higher rates of false positives and false negatives. The predicted and actual labels appear to be moderately correlated, according to the MCC of 0.796. With an NPV of 0.763, the Naive Bayes algorithm displays a relatively high rate of false negatives. It has the highest FNR of the algorithms listed, 0.185, indicating a higher rate of positive instances being incorrectly classified as positive. The predicted and actual labels appear to be moderately correlated, according to the MCC of 0.788.

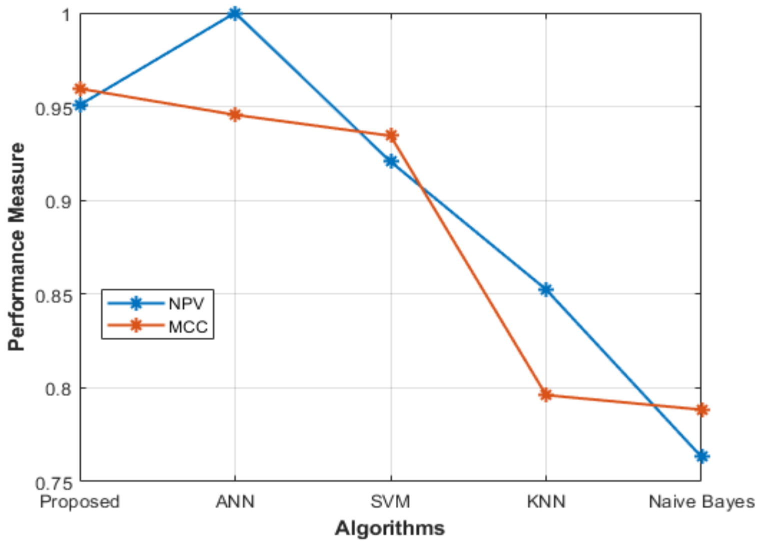

Figure 6: Performance Measures of NPV & MCC.

The NPV & MCC comparison of the proposed and existing methods is shown in the above figure 6. An NPV of 0.95 for the proposed method in the comparison between the proposed and existing methods denotes that, of all the instances that were classified as negative by the proposed method, 95% of the negative instances were correctly identified by the classifier. MCC of 0.95 for the proposed method indicates that the classifier using it is performing well in terms of balanced classification performance when taking into account all four potential outcomes. The proposed method appears to be doing a great job of correctly identifying negative instances and producing balanced classification results, as indicated by its NPV and MCC of 0.95.

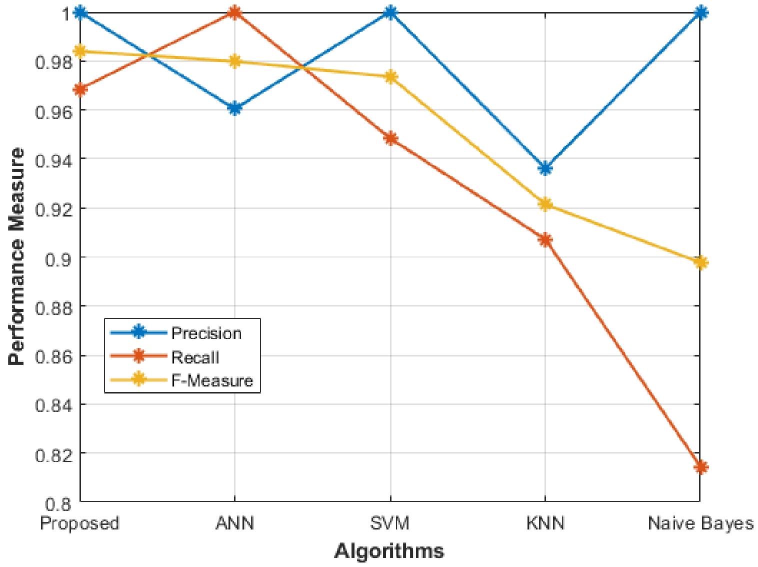

Figure 7: Performance Measures of Precision, Recall and F-Measure.

The Precision, Recall and F-Measure comparison of the proposed and existing methods is shown in the above figure 7. The Precision, Recall and F-Measure of proposed is 1, 0.968 and 0.983. A precision of 1 in the context of the proposed model denotes perfect accuracy in identifying positive instances. This implies that the model is extremely trustworthy when it predicts a positive instance, and there are no instances in which it incorrectly labels a non-fraudulent audit as fraudulent. Recall gauges a classifier's accuracy in correctly identifying every instance that qualifies as positive. The ratio of true positives to the total of true positives and false negatives is used to calculate it. The model is correctly identifying 96.8% of all actual positive instances, according to a recall value of 0.968. The proposed model has a high recall, which indicates that it successfully detects a sizeable portion of positive instances (such as fraudulent audits) in the dataset. An F-measure of 0.983 shows that the proposed model achieves high accuracy in positive predictions while also successfully identifying a large portion of positive instances, striking an excellent balance between precision and recall.

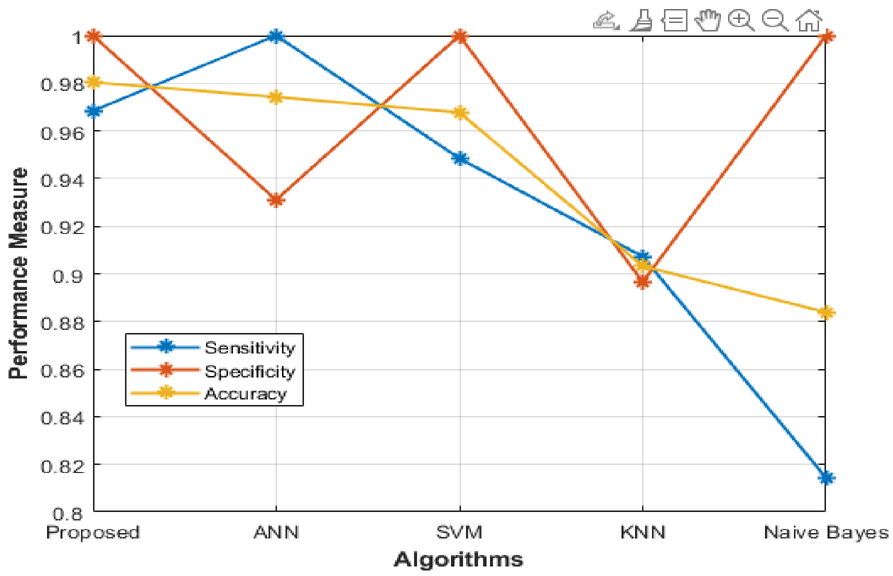

Figure 8: Performance Measures of Sensitivity, Specificity and Accuracy.

The Sensitivity, Specificity and Accuracy comparison of the proposed and existing methods is shown in the above figure 8. The Sensitivity, Specificity and Accuracy of proposed is 0.968, 1, and 0.980. According to a sensitivity value of 0.968, the proposed model successfully detects 96.8% of all real positive instances. High sensitivity value in the context of the proposed model for audit classification denotes that it accurately captures a sizable portion of positive instances (for example, correctly identifying the majority of fraudulent audits), making it extremely reliable in spotting positive cases. A specificity value of 1 indicates that all negative instances are correctly identified by the proposed model, with no false positives. A specificity of 1 in the context of the proposed model indicates that it is extremely accurate in identifying negative instances (such as non-fraudulent audits), preventing any instances where a non-fraudulent audit is mistakenly classified as fraudulent. The ratio of the sum of true positives and true negatives to the total number of instances is used to calculate accuracy. The proposed model predicts events with a 98% accuracy, as shown by an accuracy value of 0.980.

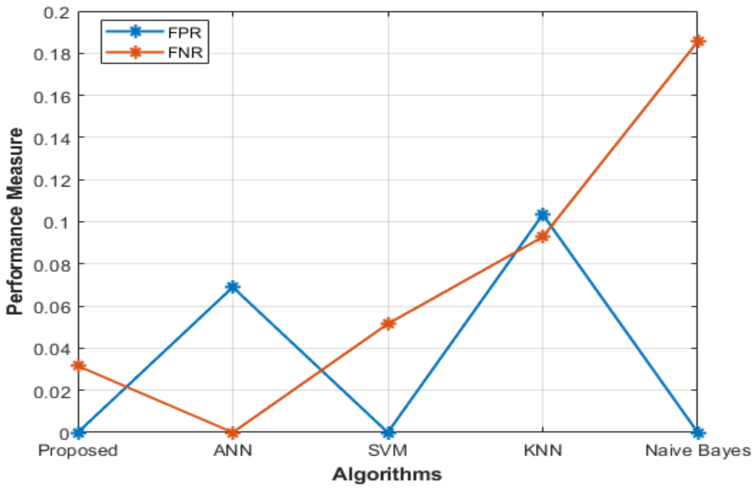

Figure 9: Performance Measures of FPR and FNR.

The FPR and FNR comparison of the proposed and existing methods is shown in the above figure 9. The FPR and FNR of proposed is 0 and 0.031. The FPR calculates the percentage of negative instances that the classifier misclassifies as positive. The ratio of false positives to the total of true negatives and false positives is used to calculate it. There are no negative instances that the suggested model has mistakenly classified as positive, according to an FPR value of 0. FNR calculates the percentage of positive instances that the classifier misclassifies as negative. The ratio of false negatives to the total of true positives and false negatives is used to calculate it. Only 3.1% of positive instances are incorrectly categorised as negative by the suggested model, according to a FNR value of 0.031.

5. Conclusion

Audit classification is the systematic process of grouping and classifying different kinds of activities, transactions, or data within the financial records or systems of an organisation. It entails the use of algorithms, statistical methods, and data analysis techniques to find patterns, anomalies, or irregularities that might point to potential fraud, non-compliance, or other risks. Using Hybrid ML, audit classification aims to automatically identify and classify items that are relevant to audits, improving the effectiveness and efficiency of the auditing process. The classification models created for audit classification take into account a number of variables, including transaction attributes, historical data, and predefined criteria, in order to accurately classify and prioritise areas for additional auditing by auditors. In the end, the objective of audit classification is to improve the identification of audit risks, facilitate targeted audits, and enhance overall financial governance and compliance within an organisation. During the pre-processing stage, the raw audit data was cleaned to remove noise and inconsistencies. From the pre-processed data, min-max normalisation and standardisation are applied to the data to ensure its robustness and comparability. The feature extraction step uses various statistical measures to gather pertinent information and characterise the audit data. Features was chosen using hybrid optimisation that is RCSO, which combines Artificial Rabbit and Sand Cat Swarm Optimisation, from the extracted data. SVM and Optimised ANN was used to process classification based on the chosen features. Because the proposed model's execution it was contrasted to existing technology, it could be guaranteed to be a technique that was more effective than the existing technique in terms of performance metrics.

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