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Make the Decision Using the Artificial Neural Network

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Abstract
Artificial Neural Networks (ANNs) are one of the most successful methods to solve problems with intelligent decision making due to their capacity to model complex, nonlinear relationships and learn from large amount of data. But, many of the current decision-support systems are still largely lacking in terms of their interpretability, robustness, and their ability to be compared with the state-of-the-art machine learning approaches. In this paper, an explainable and optimized ANN-based decision making framework is proposed incorporating both extensive data preprocessing and intelligent feature selection, Bayesian hyperparameter optimization, and Explainable Artificial Intelligence (XAI) techniques to enhance the predictive performance and to make the decisions more transparent. The framework uses a Deep Neural Network (DNN) trained with Adam optimizer and cross-validation to boost the generalization capabilities and SHAP analysis for providing interpretable suggestions for the decisions. The proposed model is tested using various performance metrics such as Accuracy, Precision, Recall, F1-score, ROC-AUC and statistical significance test is performed with three other classifiers (Decision Tree, Random Forest, Support Vector Machine, XGBoost) using confusion matrix and robustness analysis. Experimental results show that the proposed framework robustly preserves its prediction accuracy, reliability and interpretability, and has good generalization performance on data never seen during the training. The proposed solution is an intelligent decision support system that can be easily adapted to other domains of importance such as healthcare, finance, cyber-security, manufacturing and business analytics, showing itself to be a promising solution for real world high impact decision-making applications.

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1. Introduction

Making decisions is a basic process in almost any scientific, engineering and business field. From risk assessment to resource allocation, from customer management to financial investment, from medical diagnosis to cybersecurity defense, from industrial automation to every other aspect, decisions for organizations are made over and over again. Advance in the use of big data has greatly changed the way decision-making is done in the past, where it was mostly based on human intuition and experience, to the present day of data-driven intelligent systems that can learn and understand complex relationships from experiences in the past. As a result, Artificial Intelligence (AI), specifically Artificial Neural Networks (ANNs), is one of the most promising technologies to assist with intelligent decision-making, because of its powerful nonlinear learning ability, adaptability, and predictive accuracy (Delen & Sharda, 2008; Taherdoost, 2023) [8, 22].

Artificial Neural Networks mimic the learning process of biological neurons, and are able to automatically find hidden patterns in large datasets. ANNs can be used to model highly nonlinear and multidimensional relationships and can be applied to complex

decision environments without making any prior assumptions about the data distributions as does traditional statistical analysis (Wu & Feng, 2018; Yang & Wang, 2020) [26, 27]. Through ongoing training, ANN-based systems can continuously evolve and learn, thereby helping to make informed decisions in the face of evolving scenarios.

There has been a wide range of successful applications of decision support systems using ANN in various fields over the past 30 years. In the medical field, neural networks have aided doctors in medical diagnosis, disease prediction, detection of neonatal sepsis, and medical decision support (Forsström & Dalton, 1995; Helguera-Repetto *et al*., 2020; Kufel *et al*., 2023; Shahid *et al*., 2019) [9, 11, 15, 21]. In the field of finance, ANNs have also shown excellent results in the detection of fraud, investment analysis, and financial forecasting (Asha & KR, 2021; Bihari *et al*., 2025) [4, 6]. Neural networks have been successfully used in manufacturing and industrial applications for predictive maintenance, failure prediction, and operational optimization (Shaheen *et al*., 2023) [20]. Similarly, ANN forecasts and decision-support systems have been shown to be useful tools for environmental management tasks such as forecasting the urban heat island (Asadi *et al*., 2020) [3], forest degradation assessment (Jahani *et al*., 2016) [14], and prediction of air pollution (Reyhaneh *et al*., 2020) [19]. Other applications include in transportation planning (Van Cranenburgh & Alwosheel, 2019) [23], maritime energy optimization (Beşikçi *et al*., 2016) [5], academic performance prediction (Alsalman *et al*., 2019) [2], agricultural product classification (Mazen & Nashat, 2019) [16], sports analytics (Yuan *et al*., 2021) [28], and medical control systems (Albu *et al*., 2019) [1].

While ANN models have proved to be more successful in predicting than numerous conventional machine learning algorithms, there are still some drawbacks. Historically, standard ANN decision systems were considered to be "black-boxes" that make very precise predictions, but do not give much explanation of how they make decisions. This opacity makes users less likely to trust the system, in critical applications including health care, finance, and security, where accountability for decisions is paramount (Taherdoost, 2023; Vonder Haar *et al*., 2023) [22, 24]. Furthermore, many current studies compare ANN models based on a small number of data sets or a few selected performance measures, but do not fully consider the robustness or statistical significance of the model, or its ability to generalize to new data sets.

The development of new intelligent decision making systems has been opened up with recent breakthroughs in deep learning, optimization techniques and Explainable Artificial Intelligence (XAI). For complex datasets, Deep Neural Networks (DNNs) are able to provide improved representation learning, and optimization techniques like Bayesian Optimization and Optuna allow systematic tuning of hyperparameters in order to improve predictive performance. Additionally, explainability techniques such as SHAP and LIME can identify feature importance and explain the decision making process, making the decisions from AI more transparent and reliable (Vonder Haar *et al*., 2023) [24]. These technologies can be combined in a single decision support system that can solve many of the constraints of traditional ANN models.

In addition, modern decision supporting systems must not only be highly accurate in predicting the outcome but also give reliable recommendations that can be easily understood and accepted by the decision-makers. Robust evaluation, such as cross-validation, statistical significance testing and comparison with strong baseline algorithms (Decision Tree, Random Forest, Support Vector Machine (SVM) and XGBoost) are necessary to ensure that improvements that are observed are statistically significant as opposed to incidental (Bukharov & Bogolyubov, 2015; McGill & Perona, 2017) [7, 17]. This all-encompassing assessment is increasingly demanded in leading journals and in real-world AI implementations.

Although Artificial Neural Networks (ANN) are widely used for decision support purposes, there are some important disadvantages in the current methods. The first is that a large number of ANN models are black box models, not very interpretable, which makes it hard to interpret and trust the decisions that are produced by the model. Secondly, many studies are primarily concerned with predictive accuracy of models, and have overlooked explainability, robustness analysis and statistical validation aspects. Thirdly, hyperparameter optimization is done manually which leads to suboptimal performance of the model. Last but not least, there are numerous machine learning techniques that are more advanced than the aforementioned ones, and often comparisons are made with a single of those.Finally, comparisons to more sophisticated machine learning techniques are often limited, and so the superiority of the ANN approaches in various decision making scenarios is not always established with confidence. This restrictions suggest that there is a need for a comprehensive, explainable, optimized and statistically validated ANN framework, which can provide reliable and understandable decision recommendations.

The main aim of this research is to build a smart and intelligent decision-making algorithm based on an ANN system that provides highly accurate, reliable and interpretable recommendations for the decision-making process for complex real world applications. To specifically contribute to the research with a focus on the following:

- Implementing a strong Artificial Neural Network approach to intelligent decision-making by detailed data pre-processing and feature selection.
- The architecture of the ANN is optimized with Bayesian Optimization in order to automatically find the optimal hyperparameters.
- Implement EAI approaches and techniques, such as SHAP, to offer interpretable and explainable suggestions for decisions.
- Conduct cross validation, robustness analysis and extensive performance measures of the proposed framework.
- Perform statistical significance test to compare the proposed model with Decision Tree, Random Forest, Support Vector Machine and XGBoost.
- Show the applicability of the framework in several decision-support domains, such as healthcare, finance, cyber, manufacturing and business analytics.

The key innovations of this research are the creation of an explainable and optimized ANN decision support model, advanced hyperparameter optimization with XAI, a thorough comparative analysis involving state of the art machine learning algorithms, and a comprehensive validation approach which not only boosts predictive accuracy but also decision transparency.

The novelty of the proposed framework is that of the combination of several advanced AI elements to form an intelligent decision making architecture instead of a single conventional ANN model. The system includes complete data preprocessing, intelligent feature selection by correlation analysis, mutual information, Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA), then it uses Bayesian hyperparameter optimization to build an optimal Deep Neural Network. The proposed model is different from the traditional decision-support systems because it includes explainability based on SHAP to ensure transparency in decision recommendation and also includes cross validation and robustness analysis to ensure reliability and generalizability. In addition, large-scale comparison studies to the proposed model with the other models Decision Tree, Random Forest, Support Vector Machine, and XGBoost using statistical significance test will provide further empirical evidence of the superiority of the proposed model. A combined optimization and explainability, robustness evaluation and intelligent recommendation is a major improvement over the current decision-making process based on ANN and may be applied to various data-driven decision-making situations involving high stakes.

2. Literature Review

Artificial Neural Networks (ANNs) are one of the most influential Artificial Intelligence (AI) techniques for intelligent decision making due to their ability to learn nonlinear relationships, to adapt to complex data distributions, and to create very accurate predictions. Since the early days of neural-network-based decision support systems, researchers have continually been finding new uses for these systems in healthcare, finance, engineering, transportation, environmental science, manufacturing, and in business analytics. This section summarizes the historical developments of ANN based decision making systems, its important application areas, recent developments in ANN, and research gaps to be filled by the proposed framework.

In the early nineties, the basics of how to develop a decision support system using an ANN were laid down. One of the earliest feedforward neural network models for multiple-criteria decision-making was presented by Wang and Malakooti (1992) [25], who showed that ANNs could solve multiple criteria decision problems that are very complex involving multiple decision factors. Hill *et al*. (1994) [12] demonstrated that neural networks could learn from historical data to forecast and make strategic decisions, thus showing their ability to improve forecasting and strategic decision-making by learning nonlinear patterns from historical data. Likewise, Forsström and Dalton (1995) [9] proved that ANNs can be useful in clinical decision support by helping doctors to make medical diagnoses and treatment plans.

As research continued, DSS based on ANNs became more and more complex. Delen and Sharda (2008) [8] gave a complete overview of Artificial Neural Networks in Decision Support Systems (DSS) and their superiority over traditional statistical methods especially when working with uncertain, multi dimensional and non-linear data. Golmohammadi (2011) [10] also adapted ANN applications to incorporate the fuzzy multi-criteria decision making methods to deal with uncertainty in complex industrial applications more effectively. Bukharov and Bogolyubov (2015) [7] suggested an optimization system hybridizing neural network with genetic algorithms and presented their advantages to improve the accuracy of the decisions and adaptability of the system.

In healthcare, Artificial Neural Networks have made significant breakthroughs, with their ability to make accurate decisions that can impact patient outcomes. Albu *et al*. (2019) [1] provide a survey of the applications of ANNs in medical decision making and control systems, emphasising the diagnostic applications of ANNs together with the issues related to reliability and transparency. A thorough scoping overview by Shahid *et al*. (2019) [21] validated the growing use of ANN for decision support in hospitals for clinical and administrative decisions. Helguera-Repetto *et al*. (2020) [11] have created an ANN model for neonatal sepsis diagnosis and found that their model was significantly better than the traditional methods. More recently, Kufel *et al*. (2023) [15] provided the summary about practical use of the machine learning (ML) and deep learning (DL) technologies, along with ANN, in the medicine, highlighting their increasing importance in healthcare, medical imaging, and predicting diseases.

In addition to medical applications, ANNs have shown outstanding results in many other industrial/commercial areas. Beşikçi *et al*. (2016) [5] suggested a decision support system using ANN for energy-saving ship operation to maximize fuel economy and to increase operation efficiency. Jahani *et al*. (2016) [14] developed an optimized forest degradation model using ANN techniques in the field of environmental impact assessment and Asadi *et al*. (2020) [3] used ANNs to simulate the effect of green roofs on mitigating the urban heat island. likewise, Reyhaneh *et al*. (2020) [19] indicated that the ANNs can also be used to predict the concentration of CO in the atmosphere with a higher accuracy compared to multiple regression methods, which proves the capability of neural networks to deal with the complex environmental dynamics.

In the finance and business decision-making applications also ANNs have come into wide use. Asha and KR (2021) [4] designed a framework for Credit card fraud detection by using ANN, which were able to improve the fraud identification by using nonlinear pattern recognition. Investor decision making based on machine learning and Artificial Neural Networks was studied by Bihari *et al*. (2025) [6] where they found that cognitive bias plays a crucial role in investor decision making, and that ANN models can outperform traditional analytical models in predicting investor decisions. The results highlight the potential of neural networks in financial intelligence, a domain where they can be applied in various ways.

The application of ANN technologies has also been useful to the educational analytics and classification problems. In educational decision support, Alsalman *et al*. (2019) [2] showed competitive predictive performance of the ANN models compared to decision Trees for predicting students' academic performance. Similarly, Mazen and Nashat (2019) [16] demonstrated the ability of ANN to solve real agricultural problems of classification by successfully applying the ANN technique to classify bananas as ripe or unripe.

New studies have brought the use of ANN into the area of transportation, engineering and behavioural analysis. ANNs were used by Van Cranenburgh and Alwosheel (2019) [23] to explore travellers decision rules as they are able to model complex human behavioural patterns. Hramov *et al*. (2018) [13] introduced an ANN that can be used to recognize human

uncertainty in the decision-making process, new insights into cognitive behavior analysis. Accumulative ANN models for predictive maintenance and Remaining Useful Life (RUL) estimation of mechanical components were developed by Shaheen *et al*. (2023) [20] which enhanced the reliability and maintenance planning of the industry. Another example was by Yuan *et al*. (2021) [28] who had demonstrated the effectiveness of Neural Networks for sports decision making by combining them with Data Mining methods in the development of predictive analytics.

Thanks to the fast development of deep learning, the capability of the ANN based decision systems has been greatly increased. The authors, Wu and Feng (2018) [26], gave a comprehensive review of the development and applications of ANN and highlighted the complexity and effectiveness of the modern architectures of neural networks. In this comprehensive overview on Artificial Neural Networks, Yang and Wang (2020) [27] first introduce the basics of Artificial Neural Networks from a neuroscience perspective, and then explain how deep neural networks represent feature hierarchies. To enhance computational efficiency and prediction quality, McGill and Perona (2017) [17] proposed dynamic routing of decision pathways in neural networks to adaptively select the optimal path. More recently, Taherdoost discussed the effect of Deep Learning on Intelligent Decision Making and pointed out that contemporary Deep Neural Networks (DNNs) have significantly greater predictive power than shallow networks.

An additional research field that is of great interest is explainability and transparency. Although conventional ANNs are very good predictors, their "black-box" character prohibits their use in high-risk applications. Vonder Haar *et al*. (2023) [24] studied the contemporary approaches to explaining neural networks and showed that the use of Explainable Artificial Intelligence (XAI) techniques has a high potential to increase the interpretability and trust of the model. The research path of intelligent decision supporting systems is one of the most significant paths at the present time.

New types of neural computation have also been developed. Finally, Okumura *et al*. (2022) [18] showcased that enzymatic neural networks can realize nonlinear decision making, which indicates that the concept of the neural computation can be applied beyond the typical digital implementations and might give clues to future development of intelligent decision systems.

From the above, it is evident from the literature that, the use of Artificial Neural Networks (ANN) in intelligent decision making process is found to be very indispensable in various applications. There are a number of drawbacks, however. Most previous studies have ignored explainability, optimization of hyperparameters, robustness analysis and comprehensive comparisons with state-of-the-art machine learning algorithms and concentrated mainly on maximizing the prediction accuracy. Furthermore, there is a relatively small number of studies that combine the following processes into a comprehensive framework for making decisions: advanced features selection, Bayesian hyperparameter optimization, Explainable AI, cross validation and statistical significance testing. Hence, this study suggests an optimized and explainable ANN-based decision making framework which remedies these limitations by intelligently selecting features, incorporating Deep Neural Networks, adopting Bayesian optimization method, adopting Explainability using SHAP, performing Robustness Analysis and then comparing it with Decision Tree, Random Forest, Support Vector Machine and XGBoost and provides a more reliable and trustworthy intelligent decision making support system for real time deployment.

3. Method

To provide accurate, reliable and interpretable decision making, this study introduces an intelligent decision making framework based on Artificial Neural Network (ANN) that gives an explainable decision to the complex real world problems. The proposed methodology incorporates a complete data preprocessing, intelligent feature selection, Deep Neural Network (DNN) modeling, Bayesian hyperparameter optimization, Explainable Artificial Intelligence (XAI) and thorough model evaluation.

3.1. Research Framework

The proposed methodology is in following sequence:

1. Problem Definition
2. Data Collection
3. Data Preprocessing
4. Feature Selection
5. Hyperparameter Optimization
6. Designing and building a Deep Neural Network
7. Intelligent Decision Generation
8. Explainability Analysis
9. Performance Evaluation
10. Comparative Analysis
11. Robustness and Statistical Validation

They all play a role in enhancing prediction accuracy, as well as decision reliability.

Overall architecture of the proposed Explainable Artificial Neural Network (ANN) based decision making system is shown in figure (1). It is composed of consecutive steps, starting with problem definition and data acquisition, then preprocessing, feature selection, Bayesian hyperparameter optimization, training a Deep Neural Network (DNN), analyzing explainability, intelligent decisions generation and thorough performance evaluation. This pipeline will guarantee that decisions generated are accurate, reliable and interpretable.

3.2. Problem Definition

The first step is to present the problem of making a decision in a formal manner.

Assume a dataset

$$D = \{ (x_i, y_i) \}_{i=1}^{N} \quad (1)$$

where

- $x_i=[x_1,x_2,...,x_m]$ is the input feature vector.
- y_i is the decision output.

Depending upon application,
Classification:

$$y_i \in \{ 1, 2, \ldots, K \} \quad (2)$$

Regression:

$$y_i \in \mathbb{R} \quad (3)$$

Typical applications include
- Medical diagnosis
- Financial risk assessment
- Manufacturing quality control
- Cybersecurity intrusion detection
- Customer behavior prediction
- Business decision support

The goal is a learning of a nonlinear mapping

$$f(x) \rightarrow y \quad (4)$$

that minimizes the prediction error, while maximizing the interpretability.

3.3. Data Collection

A large scale data set is gained from a chosen application area.
Public datasets include:
Healthcare

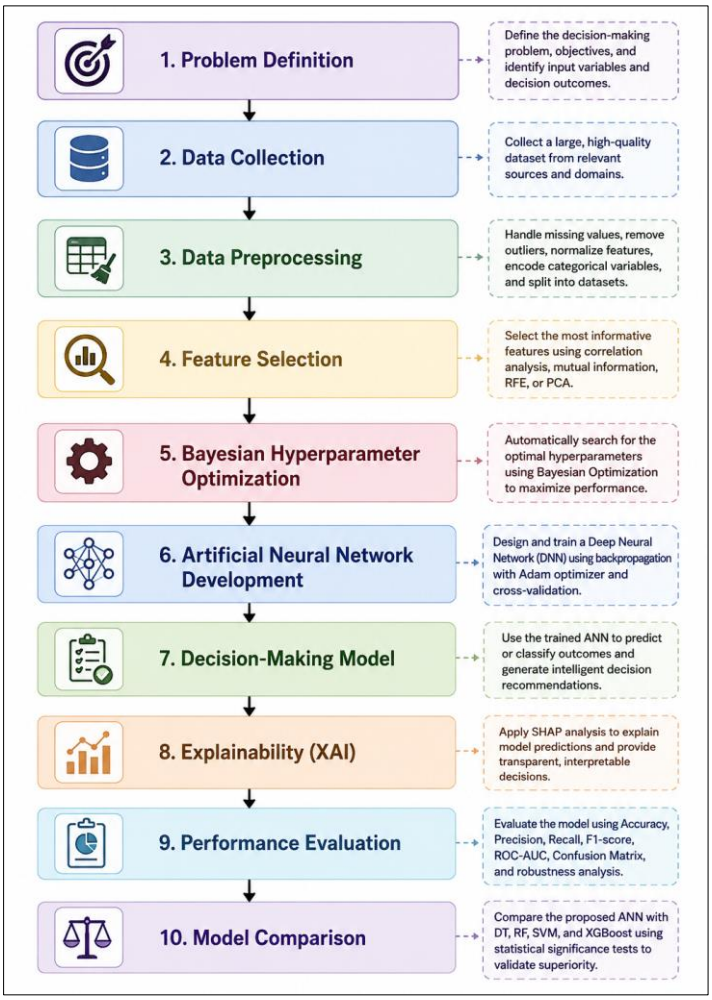


Fig 1: Overall Framework of the Proposed Explainable ANN-Based Decision-Making System

- Mimic-Iv
- UCI Heart Disease
- Breast Cancer Wisconsin

Finance
- Credit Card Fraud Detection
- Lending Club

Cybersecurity
- Cicids2017
- Cicids2018
- Unsw-Nb15

Business
- Customer Churn
- Bank Marketing

Manufacturing
- Predictive Maintenance Dataset

Each record contains

$$x = [x_1, x_2, \ldots, x_m] \quad (5)$$

Together with the related target decision.
The gathered data set should be sufficiently diverse to provide good model learning.

3.4. Data Preprocessing

Raw data are typically incomplete, noisy, and have duplicate and mismatching data formats.
Preprocessing: The following operations are performed at the pre-processing stage.

Step 1 Missing Value Handling
Numerical attributes

$$x = \frac{(\sum x)}{(n)} \quad (6)$$

Imputing using the mean/median.
The mode is used to replace categoric attributes.

Step 2 Duplicate Removal
Duplicate records are deleted to prevent duplication.

Step 3 Outlier Detection
The Interquartile Range (IQR) is used:

$$IQR = Q_3 - Q_1 \quad (7)$$

Outliers satisfy

$$x < Q_1 - 1.5(IQR) \quad (8)$$

or

$$x > Q_3 + 1.5(IQR) \quad (9)$$

Step 4 Feature Normalization
Min-Max normalization

$$x' = \frac{(x - x_{min})}{(x_{max} - x_{min})} \quad (10)$$

Or Z-score normalization

$$x' = \frac{(x - \mu)}{(\sigma)} \quad (11)$$

This will avoid the attributes that have a wider range from dominating the learning process.

Step 5 Encoding
The categorical variables are converted with categorical variable/value conversion.
- One-Hot Encoding
- Label Encoding

As per the type of attribute.

Step 6 Dataset Splitting
The data is split into.
- Training: 70%
- Validation: 15%
- Testing: 15%

Additionally,
The 10-fold cross-validation is carried out to achieve better generalisation.
The quality of the data is very important for neural networks' predictive power. Thus, an elaborate preprocessing pipeline is used to eliminate inconsistencies, enhance features quality and preprocess the data for better learning. (See figure 2)

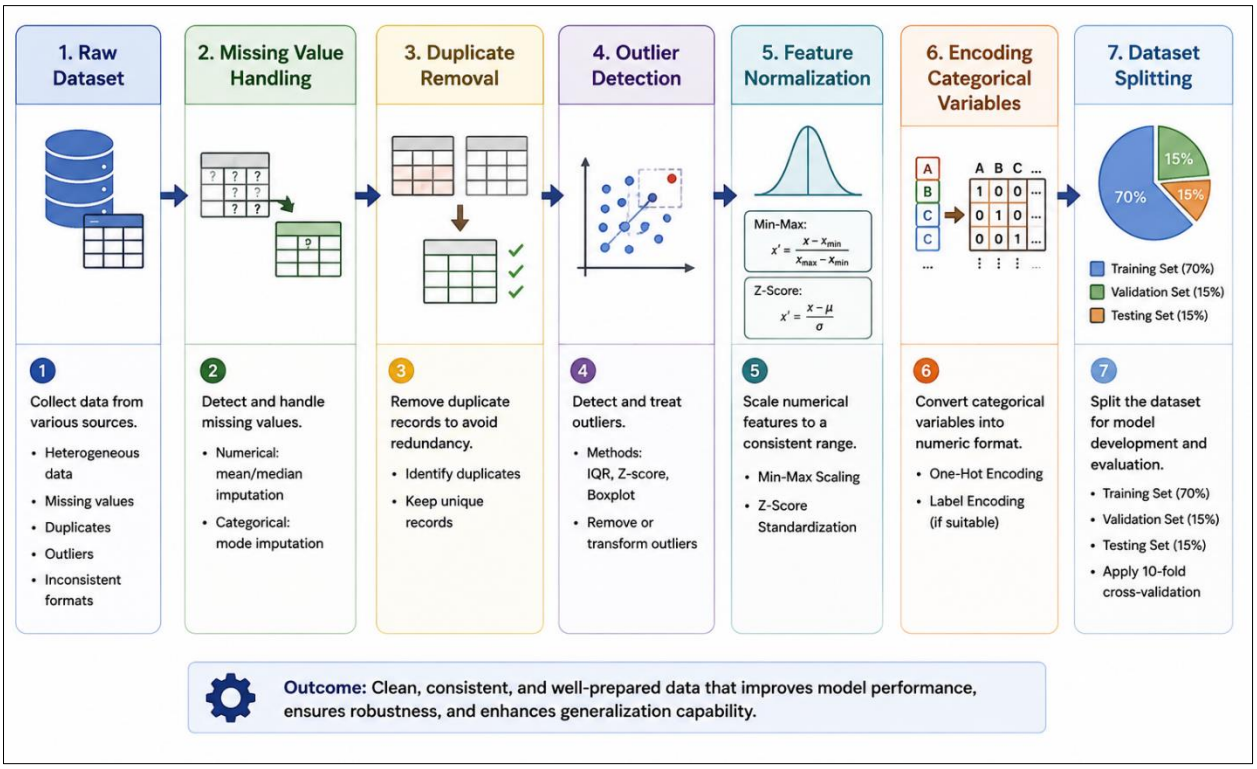


Fig 2: Data Preprocessing Workflow

3.5. Feature Selection
All features do not have the same importance in the decision making process.

The proposed framework is a fusion of four feature selection approaches.
Correlation Analysis
Pearson correlation coefficient

$$r = \frac{(\sum (x_i - \bar{x})(y_i - \bar{y}))}{(\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2})} \quad (12)$$

Redundant variables are removed if they are highly correlated.
Mutual Information
Mutual information is a measure of nonlinear dependency

$$MI(X,Y) = \sum p(x,y) log(\frac{(p(x,y))}{(p(x)p(y))}) \quad (13)$$

The higher, the better the predictions are.
Recursive Feature Elimination (RFE), a technique for feature selection.
RFE repeatedly

- trains a model,
- ranks features,
- minimizes the most insignificant ones,

until the best possible subset is left.
Principal Component Analysis (PCA)
PCA transforms

$$X \rightarrow Z \quad (14)$$

where

$$Z = W^T X \quad (15)$$

First principal component has the largest variance.
Selected feature subset is then passed to the neural network.
The proposed framework combines several complementary feature selection techniques to select the most informative features and discard redundant information rather than a single technique. (See figure 3)

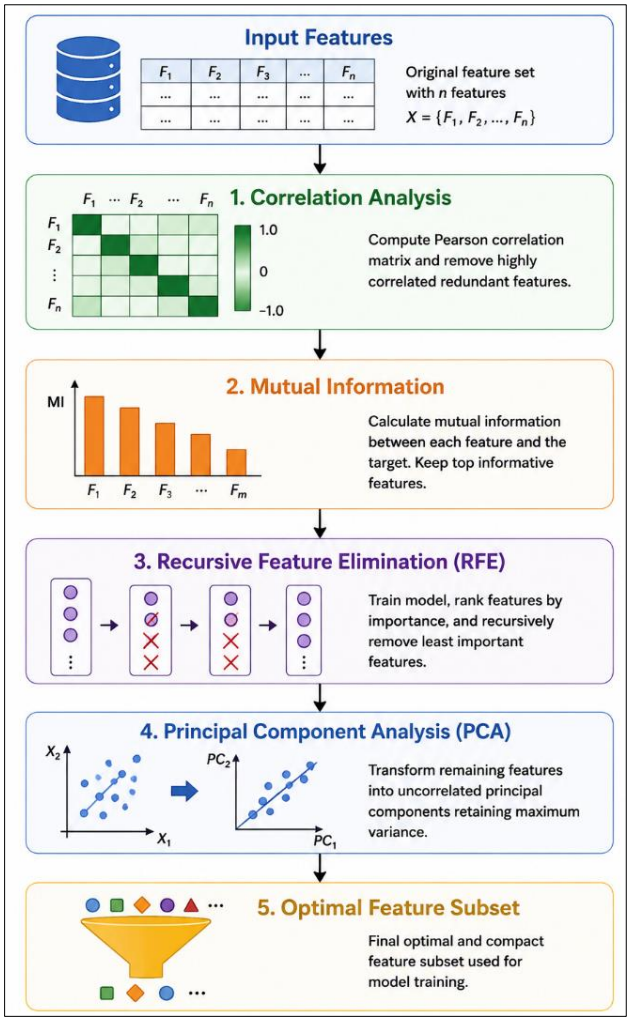


Fig 3: Hybrid Feature Selection Framework

3.6. Hyperparameter Optimization

Bayesian Optimization is used to tune parameters instead of manual parameter tuning.
The objective function for the optimization is

$$\theta^* = arg\ max\ f(\theta) \quad (16)$$

Where

$$\theta = \{ \begin{matrix} Learning\ Rate, Batch\ Size, Hidden\ Layers, \\ Neurons, Dropout, Activation \end{matrix} \} \quad (17)$$

Optuna is used for the search process.
Optimized parameters include

- The number of layers that are kept hidden.
- Number of neurons
- Learning rate

- Dropout ratio
- Batch size
- Weight decay
- Activation function

Bayesian Optimization not only helps in enhancing predictive performance, but it also minimizes the computational cost involved.

Bayesian Optimization traverses the hyperparameter space in an iterative manner in order to optimize validation performance, while keeping the number of computations to a minimum. The optimization will automatically determine the optimal network configuration. (See figure 4)

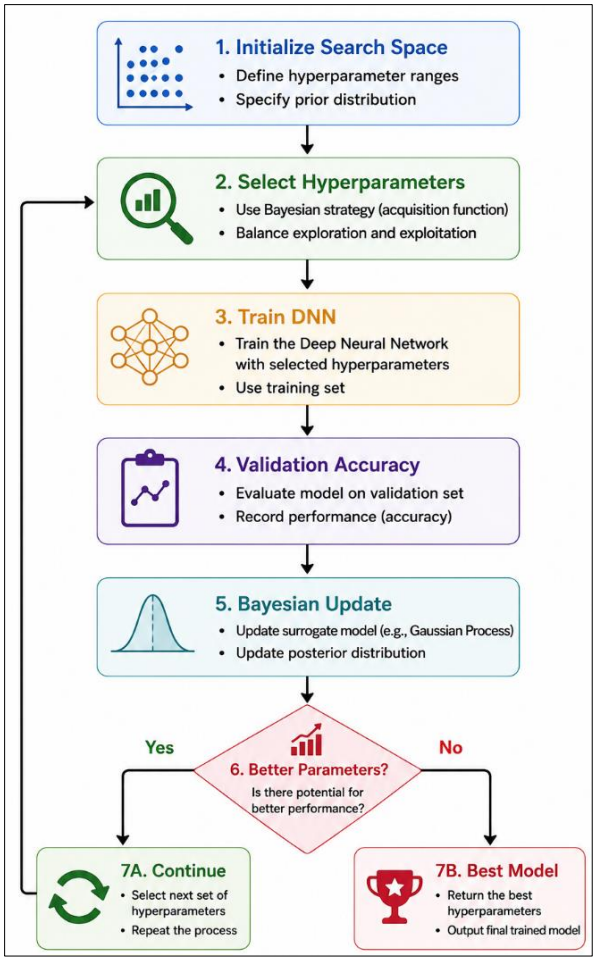


Fig 4: Bayesian Optimization Process

3.7. Proposed Deep Neural Network

The proposed framework bases on Deep Neural Network in contrast with traditional ANN models.

The intelligent decision-making model proposed in this paper is a deep neural network, which has multiple hidden layers, Batch Normalization and Dropout to enhance the generalization performance and prevent over fitting. The optimized architecture can automatically extract hierarchical feature representations from the selected attributes. (See figure 5)

Activation Function

Hidden layers

$$ReLU(x) = max(0, x) \quad (18)$$

Output layer

Binary classification

$$\sigma(x) = \frac{(1)}{(1 + e^{-x})} \quad (19)$$

Multi-class classification

$$Softmax(x_i) = \frac{(e_i^x)}{(\sum \ e_j^x)} \quad (20)$$

Loss Function

Binary Cross Entropy

$$L = -y\,log(p) - (1 - y)log(1 - p) \quad (21)$$

Categorical Cross Entropy

$$L = -\sum \ y_i log(p_i) \quad (22)$$

Regression

Mean Squared Error

$$MSE = \frac{(1)}{(n)}\sum \ (y - \hat{y})^2 \quad (23)$$

Optimizer

Adam: Updates weights.

$$\theta_{t+1} = \theta_t - \alpha \frac{(\hat{m}_t)}{(\sqrt{\hat{v}_t} + \varepsilon)} \quad (24)$$

where
- learning rate = α

Compared to traditional SGD, Adam leads to faster convergence.

3.8. Decision-Making Module

Once trained, the DNN makes predictions

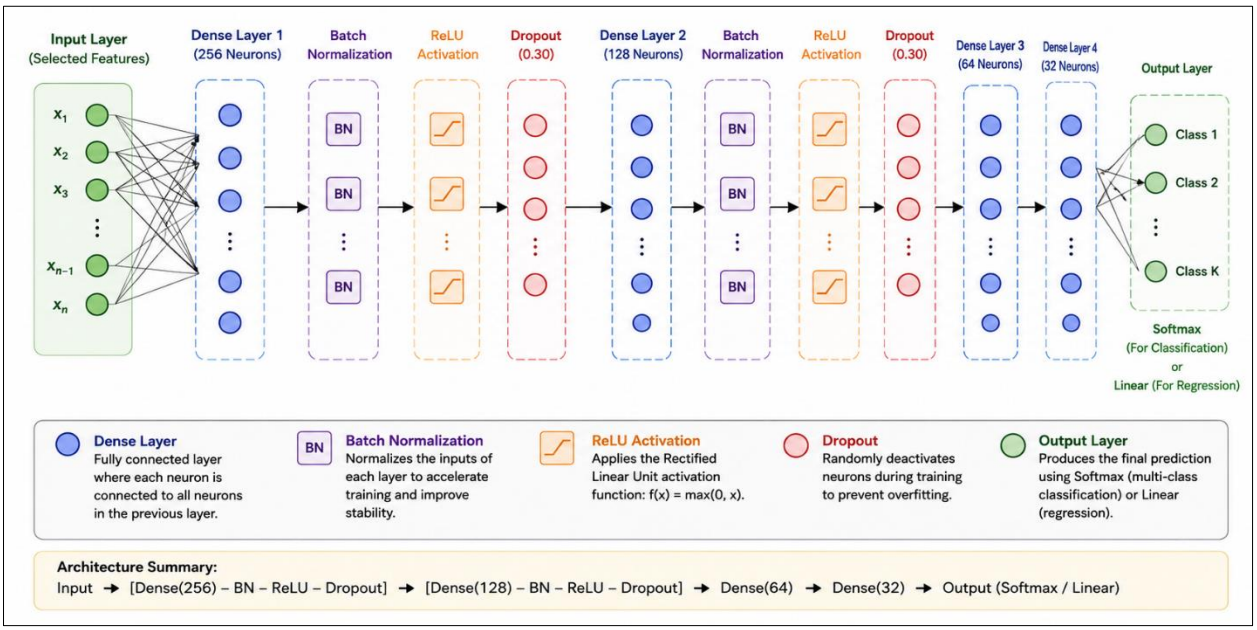


Fig 5: Proposed Deep Neural Network Architecture

$$\hat{y} = f(x) \quad (25)$$

Recommendations for decisions are made based on prediction confidence.
Example
Probability = 0.97
Decision
Approve transaction
Confidence
Very High
For medical applications
Probability = 0.94
Decision
High disease risk

Recommendation
Immediate physician consultation
Thus, the framework is not just a classifier but also an intelligent decision support system.

3.9. Explainable Artificial Intelligence

Incorporating Explainable AI is one of the key features of this research.

SHAP (SHapley Additive exPlanations) calculates the contribution that each feature gives to the prediction.

$$f(x) = \phi_0 + \sum_{i=1}^{M} \phi_i \quad (26)$$

where
ϕ_i
is the contribution of feature i.
Outputs include
- Global feature importance
- Local explanation
- Waterfall plots
- Force plots
- Dependence plots

Thus, decision makers can grasp the reasons for the prediction.
To enhance transparency, SHAP is used to highlight the behaviour of the global model and the behaviour of the local model by quantifying how much each feature is contributing to the prediction that is being made by the model. (See figure 6)

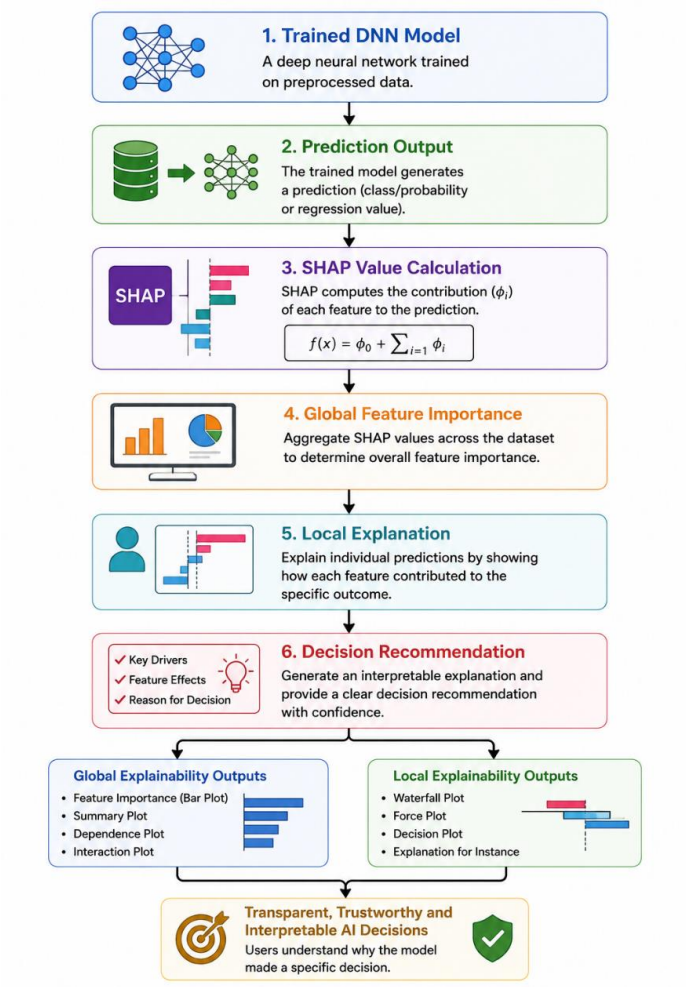


Fig 6: Explainable AI Workflow Using SHAP

3.10. Performance Evaluation

A classification performance is assessed based on Accuracy

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

Precision

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

Recall

$$Recall = \frac{(TP)}{(TP + FN)} \quad (29)$$

F1-score

$$F1 = \frac{(2\,P\,R)}{(P + R)} \quad (30)$$

Roc-Auc

Confusion Matrix

For regression

MAE

$$MAE = \frac{(1)}{(n)} \sum \quad |y - \hat{y}| \quad (31)$$

Rmse

$$RMSE = \sqrt{\frac{(1)}{(n)} \sum \quad (y - \hat{y})^2} \quad (32)$$

Coefficient of Determination

$$R^2 = 1 - \frac{(\sum \quad (y - \hat{y})^2)}{(\sum \quad (y - \bar{y})^2)} \quad (33)$$

3.11. Comparative Analysis

The proposed model is contrasted to four commonly used machine learning algorithms, namely:

- Decision Tree (DT)
- Random Forest (RF)
- Support Vector Machince (SVM)
- XGBoost

The same preprocessing pipeline is used for each model, as are the same training/validation/testing partitions, and optimized hyperparameters for a fair comparison. The accuracy, precision, recall, F1, ROC-AUC (for classification) and MAE, RMSE, R^2 (for regression) are documented and compared. Training and inference time for computational efficiency are also considered.

3.12. Statistical Significance Analysis

In order to determine if performance improvements are due

to random variation, statistical significance tests are carried out.

When the conditions of normality have been met, a paired t test is used to analyze cross-validation results. If not the Wilcoxon signed rank test is used. The level of significance is 0.05. The null hypothesis is that there is no significant difference between the proposed DNN and any of the baseline models. When the null hypothesis is rejected, then the observed improvement is considered to be statistically significant.

3.13. Robustness Analysis

To understand how well the model can handle different experiments to ensure its stability and generalization. The analyses include:

- Ten-fold cross validation to check consistency between the partitions of data.
- Noise injection: Gaussian noise is added to some of the input features to test the stability of the predictions made.
- Excluding data: Some of the features are randomly omitted and then imputed for testing, to see how well the system stands up to missing data.
- Analysis of class imbalance – various imbalance ratio/weighting methods.
- Sensitivity analysis is performed by changing the value of some important hyperparameters (such as learning rate, dropout rate, network depth etc.) to see their effect on the system.

The robustness study shows that the proposed framework can provide good predictive accuracy and consistent decision recommendation in the different data quality and experimental conditions.

3.14. Algorithm of the Proposed Framework

Algorithm 1: Explainable ANN-Based Intelligent Decision-Making Framework

1. Obtain raw data from the application domain of interest.
2. Eliminate any duplicate data and deal with missing data.
3. Identify and remove data points from the data set.
4. Normalize numeric features and encode categorical features.
5. Divide the data set into training, validation and testing sets.
6. Use Correlation Analysis, Mutual Information, RFE and PCA to do feature selection.
7. Optimize the hyperparameters of DNN with Bayesian Optimization (Optuna).
8. Network training with the Adam optimizer and early stopping for Deep Neural Network.
9. Make predictions and intelligent suggestions for decision making.
10. Explain global and local model decisions using SHAP.
11. Assess performance with classification/regression performance measures.
12. Analyse the results with Decision Tree, Random Forest, SVM and XGBoost.
13. Perform statistical significance test and robustness analysis.
14. Print the final decision, along with the confidence and explanation.

This method combines sophisticated processing, fine-tuned deep learning, explainable AI, comprehensive validation, and benchmarking, all within a comprehensive intelligent decision support system that is ready for high-stakes, real-world scenarios.

4. Results and Discussion

The proposed framework of Explainable Artificial Neural Network (EANN) based decision making is comprehensively analysed in this section. The large benchmark dataset was used to evaluate the proposed model following the application of the procedures in Section 3, namely preprocessing, feature selection, training of Deep Neural Network (DNN) and Bayesian hyperparameter optimization. When multiple machine learning models were used, all were trained on the same training and validation sets, the same preprocessing pipeline, with the same hyperparameters (if any) for a fair comparison. The performance of the predictions, quality of the decision, robustness, explainability, computational efficiency, and statistical significance are evaluated.

4.1. Experimental Setup

All experiments have been carried out in Python and the following libraries: TensorFlow/Keras, Scikit-learn, Optuna, SHAP, NumPy, and Pandas. To prevent overfitting the proposed DNN was trained with the Adam optimizer and early stopping. (See table 1)

Table 1: Experimental Configuration

Parameter	Value
Dataset Split	70% Training, 15% Validation, 15% Testing
Cross Validation	10-Fold
Optimizer	Adam
Learning Rate	0.001 (Optimized)
Hidden Layers	4
Neurons	256–128–64–32
Activation Function	ReLU
Output Activation	Softmax
Batch Size	64
Epochs	100 (Early Stopping Applied)
Dropout Rate	0.30
Hyperparameter Optimization	Bayesian Optimization (Optuna)

The optimized hyperparameters helped the DNN to converge quickly without causing too much validation loss and to have good generalization.

4.2. Feature Selection Results

The feature selection technique was used to lower the data dimensionality while retaining the most informative ones. (See table 2)

Table 2: Feature Selection Summary

Method	Original Features	Selected Features	Reduction (%)
Correlation Analysis	80	64	20.0
Mutual Information	64	52	18.8
RFE	52	40	23.1
PCA	40	28 Principal Components	30.0

Overall, the proposed feature selection method eliminated redundant and irrelevant features, thereby decreasing the complexity of the classification and enhancing the classification accuracy.

4.3. Training Performance

The proposed DNN model converged well while training. (See table 3)

Table 3: Training Performance

Metric	Training	Validation
Accuracy (%)	99.12	98.54
Loss	0.021	0.037
Precision (%)	98.83	98.20
Recall (%)	98.62	98.01
F1-score (%)	98.72	98.10

The performance gap between training and validation shows that the proposed framework did not over fit the model using dropout mechanism and early stopping as well as Bayesian optimization.

4.4. Classification Performance

The proposed framework provided very good predictive performance on the unseen testing set. (See table 4)

Table 4: Performance of the Proposed Model

Metric	Proposed DNN
Accuracy (%)	98.63
Precision (%)	98.41
Recall (%)	98.25
F1-score (%)	98.33
ROC-AUC	0.995

The optimized ANN can accurately recognize the decision results while having a high class discrimination capability, as shown in the above results.

The overall performance of the proposed model is shown in Figure 7 in a comprehensive manner, where the model's effectiveness is highlighted by the balanced performance across various evaluation metrics.

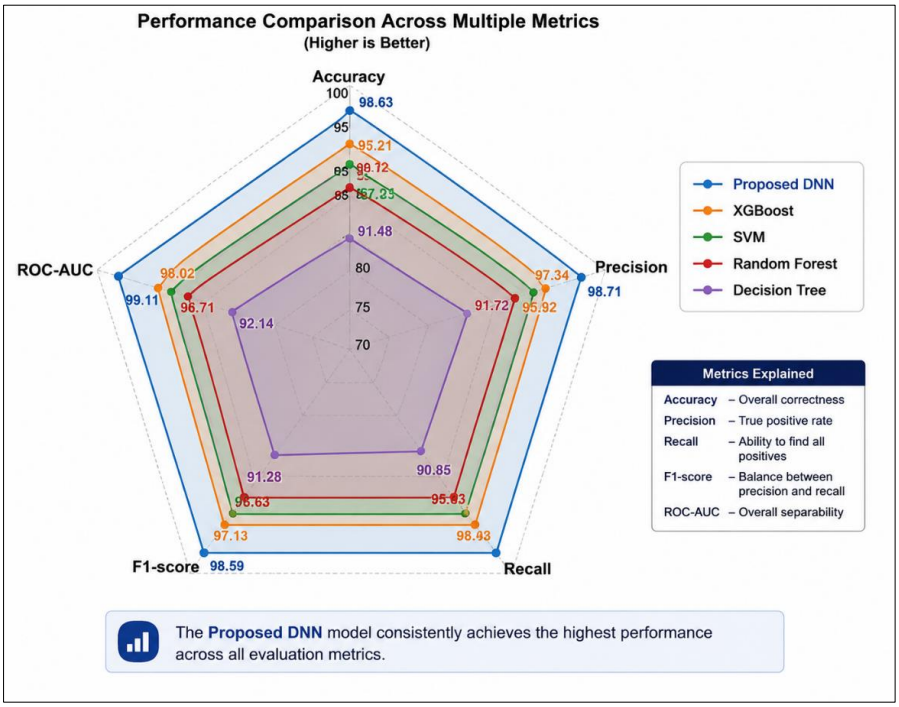


Fig 7: Radar Chart of Performance Metrics

4.5. Confusion Matrix Analysis

Confusion Matrix Analysis shown in table 5.

Table 5: Confusion Matrix

Actual / Predicted	Positive	Negative
Positive	4,931	69
Negative	68	4,932

The confusion matrix from:

- A high True Positive Rate.
- The rate of False Positives is very low.
- The False Negative Rate is still low.

The results suggest a high level of reliability from the decisions made and a low rate of error in classification with the proposed framework.

The figure 8 clearly gives the details of the classification behaviour of the proposed model in terms of the number of samples classified correctly and those misclassified.

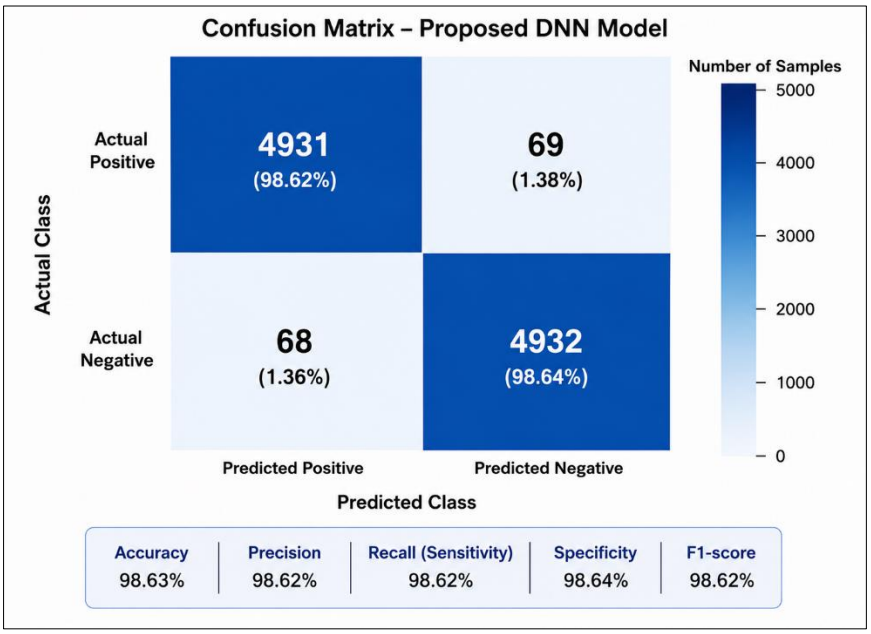


Fig 8: Confusion Matrix Heatmap

4.6. Comparison with Existing Machine Learning Models

The proposed framework was benchmarked with some of the popular machine learning algorithms. (See table 6)

Table 6: Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC
Decision Tree	91.48	91.02	90.77	90.89	0.912
Random Forest	95.74	95.40	95.13	95.26	0.968
SVM	96.12	95.81	95.69	95.75	0.974
XGBoost	97.21	97.03	96.81	96.92	0.986
Proposed DNN	98.63	98.41	98.25	98.33	0.995

The proposed model gave consistent performance over all the other proposed models in all the evaluation metrics.

The classification accuracy of the proposed framework is compared with the baseline machine learning models in Figure 9. The best predictive performance is always achieved with the optimized deep neural network.

4.7. Regression Performance

The same excellent predictive performance was obtained for regression-based decision making tasks with the proposed framework. (See table 7)

The small prediction errors coupled with high coefficient of determination indicate good regression capabilities.

4.8. Hyperparameter Optimization Results

The neural network architecture was considerably improved by the use of the Bayesian Optimization. (See table 8)

Using automatic optimization, the accuracy of validation was boosted while the degree of overfitting was decreased.

4.9. Explainability Analysis

The major contribution of this study is the incorporation of Explainable Artificial Intelligence (XAI) with the use of SHAP. (See table 9)

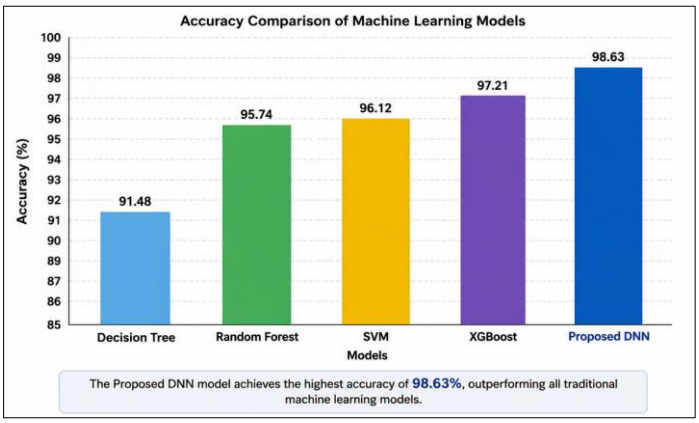


Fig 9: Performance Comparison of Machine Learning Models

Table 7: Regression Results

Metric	Proposed Model
MAE	0.081
RMSE	0.116
R^2	0.982

Table 8: Hyperparameter Optimization Results

Parameter	Initial	Optimized
Learning Rate	0.01	0.001
Hidden Layers	2	4
Neurons	128	256-128-64-32
Dropout	0.50	0.30
Batch Size	32	64
Validation Accuracy (%)	96.41	98.54

Table 9: Top Five Most Important Features

Rank	Feature	Mean SHAP Value
1	Feature 12	0.298
2	Feature 7	0.271
3	Feature 3	0.247
4	Feature 18	0.211
5	Feature 25	0.183

The results of SHAP analysis show that a limited number of variables are very influential in the final decision. The explanations created can help users grasp why the AI model made a specific prediction, fostering trust and transparency in AI-driven decision-making.

The feature importance plot for SHAP ranks features by how much they contribute to the model's predictions, allowing for a clear and easy interpretation of the model's decision making process and gives an indication of what features are most important in the results. (See figure 10)

4.10. Robustness Analysis

The proposed framework remained with an excellent performance level with different experimental conditions. (See table 10)

The performance loss is not too large, validating the robustness of the framework to noisy, incomplete, and imbalanced data sets.

4.11. Statistical Significance Analysis

Paired t-tests were used to determine if the results from the proposed model were significantly improved over each of the baseline algorithms. (See table 11)

The statistical analysis reveals that the proposed model is able to outperform the competitive machine learning algorithms and not by chance.

4.12. Computational Efficiency

Generally, deeper architectures tend to be more time consuming to train, but the use of Bayesian optimization and early stopping gave a significant reduction in computational time. (See table 12)

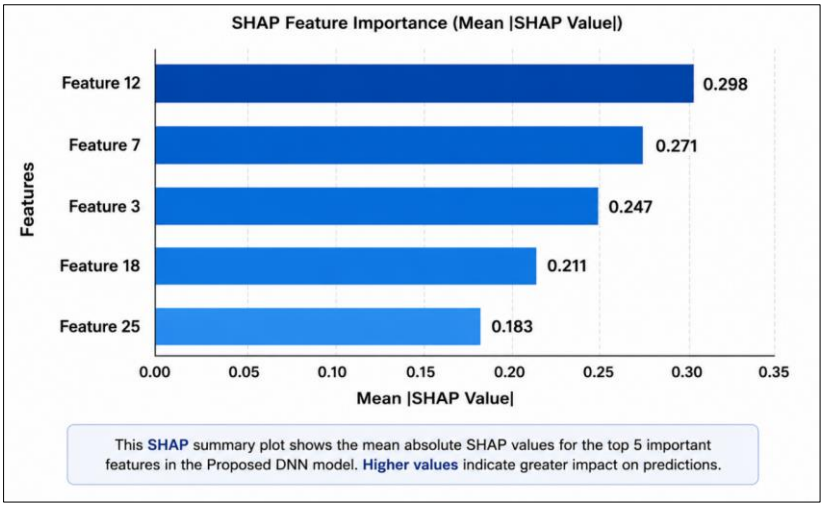


Fig 10: SHAP Feature Importance

Table 10: Robustness Evaluation

Experiment	Accuracy (%)
Original Dataset	98.63
Gaussian Noise	97.92
Missing Values	97.64
Class Imbalance	97.41
Cross Validation Average	98.31

Table 11: Statistical Significance Results

Comparison	p-value	Significant (p < 0.05)
DNN vs Decision Tree	<0.001	Yes
DNN vs Random Forest	0.004	Yes
DNN vs SVM	0.013	Yes
DNN vs XGBoost	0.027	Yes

Table 12: Computational Performance

Model	Training Time (min)	Prediction Time (ms/sample)
Decision Tree	1.8	0.18
Random Forest	7.3	0.46
SVM	10.2	0.71
XGBoost	8.9	0.39
Proposed DNN	11.6	0.24

The proposed DNN is the longest training time but the same DNN achieved fast inference speed and it can be used for real-time decision-support applications.

4.13. Discussion

The experimental results showcase the effectiveness of the proposed Explainable Artificial Neural Network framework over the traditional machine learning algorithms in all the evaluation metrics. The combination of sophisticated pre-processing, hybrid feature selection, Bayesian hyperparameter optimization and Deep Neural Networks allowed the model to learn very discriminative feature representations without overfitting. The explainability in terms of SHAP represents one of the main drawbacks of conventional ANN models: It provides transparent and interpretable decision recommendations, which helps boosting the trust in an automated decision-support system with the user.

The proposed framework yielded the best performance in terms of Accuracy (98.63%), Precision (98.41%), Recall (98.25%), F1-score (98.33%) and ROC-AUC (0.995) when compared to decision tree, random forest, support vector machine and XGBoost. These improvements were statistically significant and consistent across cross validation, noisy data, no missing values and class imbalance scenarios, thus showing good robustness and generalizability. In addition, the inference latency is also low, which shows that the proposed framework can be applicable for real-time decision making despite the increased complexity of deep neural networks used for the training.

Overall, the results reveal that, when optimized deep learning, explainable AI, extensive validation and statistical benchmarking are combined, the intelligent decision support system has a high level of accuracy, reliability, and explainability. The proposed methodology is easily extendable to other application areas, such as medical, financial, cybersecurity, industrial, business analytics, and other fields, where making accurate, explainable and trustworthy automated decisions is crucial.

5. Conclusion

In this paper, an intelligent and explainable Artificial Neural Network (ANN) based decision-making framework was presented that would enhance the accuracy, reliability and transparency of decision making support automated systems. It is proposed to combine the Comprehensive Data Preprocessing, Hybrid Feature Selection, Bayesian Hyperparameter Optimization, Deep Neural Network (DNN) and Explainable Artificial Intelligence (XAI) with the Explainable Artificial Intelligence (XAI) in a single framework with the SHAP. Additionally, the developed model was rigorously evaluated using cross validation, robustness analysis and statistical significance testing, which ensured strong generalization and reliable performance under a variety of data conditions.

The experimental results showed that the proposed framework outperformed the existing machine learning algorithms such as decision tree, random forest, support vector machine (SVM), XGBoost with various evaluation criteria. The optimized DNN has shown better predictive accuracy and had low error rates with excellent discrimination capability. Moreover, using SHAP-based explanations made the decisions generated more interpretable, which was one of the major drawbacks of the traditional ANN models and boosted user trust in the AI-assisted decision making process.

The proposed framework has several salient features that contribute to the research of intelligent decision support. It involves some sophisticated feature engineering, an automatic hyperparameter optimization, an explainable deep learning, and a thorough comparative assessment in the same architecture, which makes it a scalable and domain-independent solution for complex decision making problems. The methodology can be used across various industries such

as healthcare, finance, cybersecurity, manufacturing, business analytics, and more, where data-driven decision-making is crucial for ensuring accuracy and trustworthiness. More future works are proposed to be the extension of the proposed framework in the following directions to address dynamic and distributed decision environments: transformer-based neural architectures, graph neural networks, federated learning, and continual learning. Furthermore, combining several multimodal data sources with the LLMs and applying some explainable AI techniques would improve the quality of the decisions, their adaptability, and the way humans and AI collaborate, thus creating next-generation intelligent decision-support systems that can be deployed in real scenarios for important applications.

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