



Research Paper

An Explainable Neural Oblivious Decision Ensemble Learning for Baldness Prediction Using Multidimensional Risk Factors

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ABSTRACT

Background: Baldness is characterized by significant hair loss on the scalp and can be influenced by factors such as age, lifestyle, genetics, and personal habits. Explainable artificial intelligence methods can help address this issue by showing the factors that contribute to individual predictions. Therefore, this study proposes an Explainable Risk-Based Baldness Prediction model using Neural Oblivious Decision Ensembles (XRB-NODE). The proposed model is an ensemble-based framework for baldness prediction that incorporates multidimensional risk factors, including genetic, medical, lifestyle, nutritional, environmental, and demographic characteristics.

Methods: An Improved ReliefF method is applied to select the most relevant factors associated with baldness classification. Subsequently, the selected features are used as input to the neural oblivious decision ensembles model, which categorizes individuals by baldness risk. Moreover, the model is trained using the AdaBelief optimizer to improve learning performance. In addition, SHAP is integrated to explain the model's prediction by showing how individual risk factors contribute to the predicted baldness category.

Results: The proposed XRB-NODE methodology was evaluated on the Baldness Risk Factor Dataset and achieved 95.06% accuracy in baldness risk classification.

Conclusion: The proposed XRB-NODE method offers accurate and interpretable baldness risk prediction, supporting modified, faster risk assessment and preventive decision-making.

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Introduction

Hair loss or baldness can cause substantial damage to the mental health and overall well-being of a patient, thereby resulting in problems such as social anxiety, lower self-confidence levels, and mental anguish. In healthcare institutions, the Basic and Specific (BASP) classification method is commonly used to evaluate hair loss by categorizing the scalp into structured areas [1]. In recent times, artificial intelligence (AI) has emerged and been applied to enhance the accuracy and reliability of alopecia diagnosis in clinical environments. In particular, machine learning (ML)-based methods provide promising solutions and enable accurate classification of damaged and healthy scalp tissue, thereby enabling timely detection of hair loss [2]. Hence, the timely detection of hair loss is important, as it helps patients take precautions, make informed decisions about hair-care treatments, and prevent severe hair loss. These AI-powered automated techniques support timely detection, improve clinical decision-making, and enable cost-effective laboratory testing. Explainable AI (XAI) has gained significant attention to improve reliability and interpretability in clinical settings.

Maben et al. [3] developed an ML-based technique for predicting hair baldness or hair loss using a labeled dataset derived from clinical and behavioral measures, including stress, medical conditions, undernutrition, hormones, and genetics. Xi et al. [4] developed an innovative AI-based technique that integrates an area ratio metric to provide a reliable evaluation of Male pattern hair loss (MPHL). Kim et al. [5] reported recent techniques for predicting hair baldness and hair-loss medications. Dachawar et al. [6] developed an innovative model that plays a significant role in supporting timely diagnosis using trichoscopy, scalp dermatoscopy, and digital imaging. Zaman et al. [7] designed an innovative framework that combines a DL approach with XAI methods to develop a multiclass model for predicting hair loss conditions. Pinon et al. [8] introduced a framework that integrates DL models and XAI methods to detect and classify hair-baldness using dermoscopic images. Behal et al. [9] developed a DL-based framework to learn complex patterns in dermoscopic images.

Although DL methods can achieve better predictive performance, their black-box nature makes it difficult to understand how the final prediction is obtained. For baldness prediction, this limitation is significant because numerous risk factors may influence an individual's baldness risk in different ways. To address

these challenges, this research work presents an Explainable Risk-Based Baldness Prediction Using Neural Oblivious Decision Ensembles (XRB-NODE) model. The primary goal of this study is to develop an explainable model to classify baldness risk based on various risk factors. The study's core contributions are summarized.

- Utilize an Improved ReliefF strategy to identify the most relevant features from the available baldness risk factors, retaining those that contribute to the classification process.
- Design a Neural Oblivious Decision Ensemble (NODE) to learn the relationships among the selected features and categorize individuals based on their baldness risk.
- Integrate the AdaBelief optimizer for model training to achieve stable and efficient parameter updates during the learning process.

Employ SHAP-based XAI to quantify the contribution of individual risk factors and provide a clear interpretation of the baldness classification results.

Materials and Methods

The proposed model follows a multistage pipeline for baldness risk prediction using deep learning techniques. The overall process of the proposed methodology is represented in Figure 1.

Data Preprocessing

Data preprocessing is performed using data cleaning, missing-value imputation, duplicate removal, one-hot encoding, and RobustScaler to prepare the dataset for further analysis. To identify missing values, inconsistent entries, duplicate records, and irrelevant information, the dataset is examined first. During model training, duplicate records are eliminated to ensure that similar observations do not occur more than once.

Feature Selection using Improved ReliefF

For baldness prediction based on risk factors, Improved ReliefF is used to identify features that have robust relationships with diverse baldness-risk categories [10]. In the improved ReliefF, each neighbor's contribution is weighted by its distance from the reference instances. A closer neighbor is assumed to have a larger weight that is determined by:

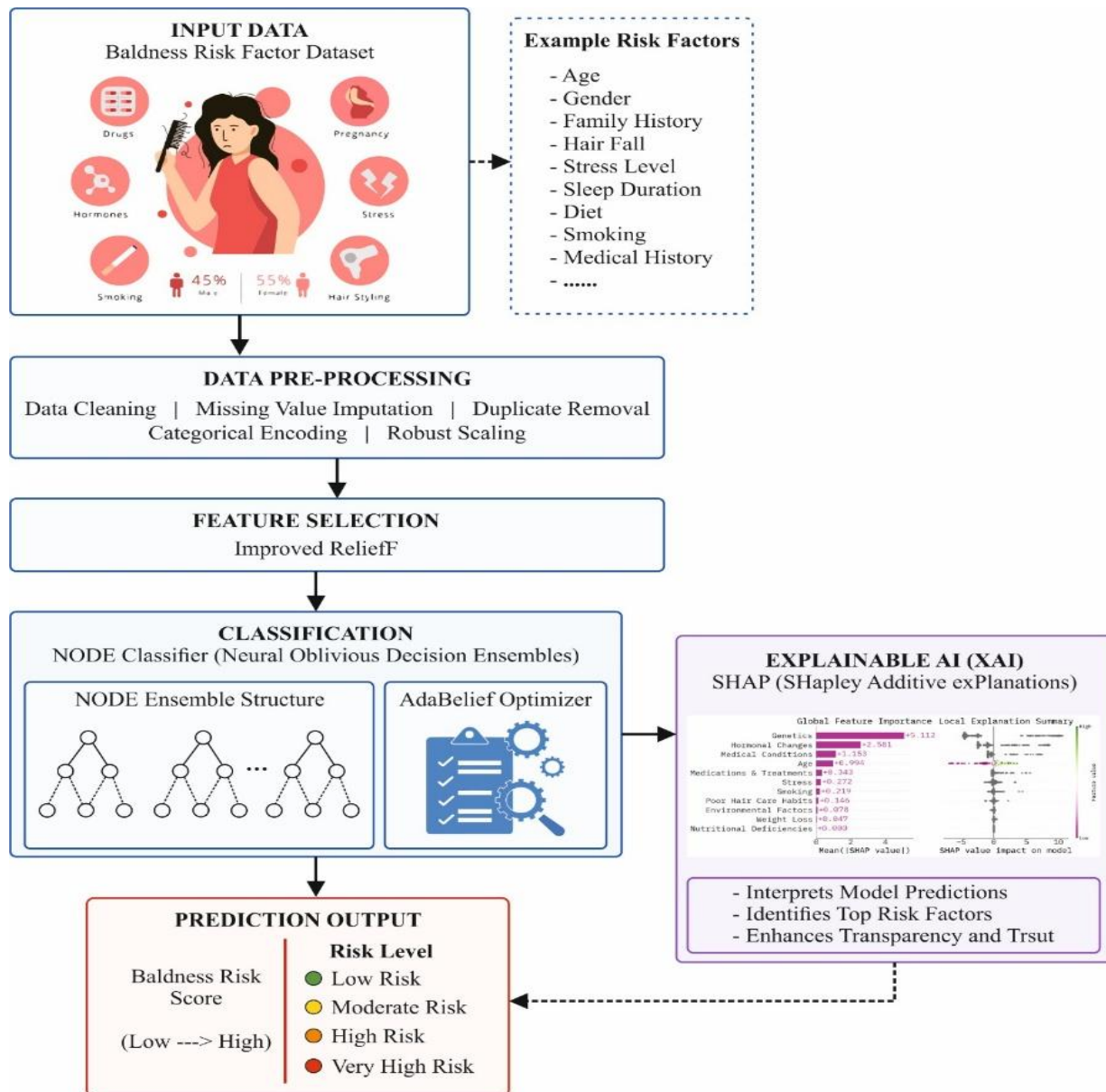


Figure 1. Overall process of the proposed methodology.

$$\alpha_{RH} = \frac{1}{d(R, H) + \epsilon} \quad (1)$$

Here the term $d(R, H)$ is the distance between the neighboring and reference instances, and a small constant avoids division by zero. The distance-weighted variances for hit and miss instances can be determined as:

$$\begin{aligned} Diff_{hit,j} &= \frac{\sum_H \alpha_{RH} diff(R, H, j)}{\sum_H \alpha_{RH}}, Diff_{miss,j} \\ &= \frac{\sum_H \alpha_{RM} diff(R, M, j)}{\sum_M \alpha_{RM}} \end{aligned} \quad (2)$$

Later, the feature weight is updated by applying the variance between miss and hit contributions.

$$W_j^{new} = W_j + Diff_{miss,j} - Diff_{hit,j} \quad (3)$$

From this expression, W_j characterizes the existing weight corresponding to the feature. The procedure is repeated for a specified number of iterations, and the final feature weights are used to rank the risk factors. Features with greater weights are preserved as the most significant features for baldness-risk prediction.

NODE-based Baldness Classification Module

For Baldness Prediction based on risk factors, individuals are assigned to predetermined baldness-risk classes using available risk factors. Meanwhile, the dataset includes tabular data; NODE is used to capture relationships among these features and assign each

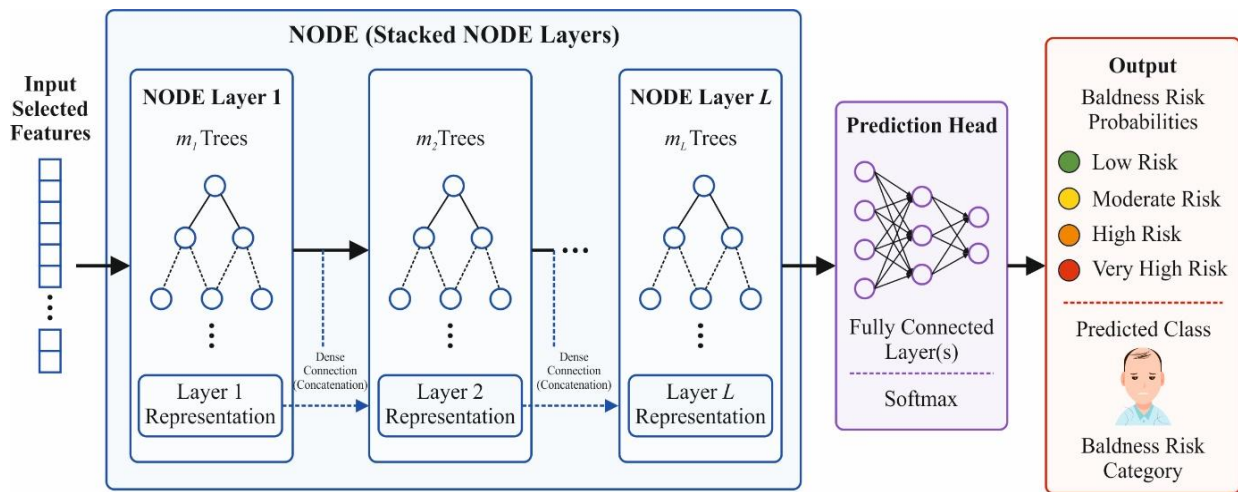
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Figure 2. Structure of NODE module.

individual to the appropriate risk category [11]. The NODE module follows a multi-layer scheme inspired by DenseNet, where outputs from earlier layers are concatenated and passed to deeper layers. This permits the model to learn shallow and deeper patterns, whereas the tree outputs can be combined for the final prediction. The mathematical expression of l_{th} NODE layer is determined by:

$$H_l = \text{Concat}(H_{l-1}, T_l) \quad (4)$$

From this expression, H_l denotes the output representation with respect to the l_{th} layer, and T_l indicates the respective tree output. This concatenation preserves information from earlier NODE layers, while deeper layers capture additional patterns. The key hyperparameters comprise the tree counts per layer, the number of layers, tree depth, the dimension of the tree outputs, and the value of α in entmax. Figure 2 illustrates the structure of the NODE module.

In the existing baldness-risk classification method, the final NODE representation is used to determine the probability for each class. The predicted baldness-risk class can be selected as

$$\hat{c} = \arg \max_{c \in \{1, \dots, C\}} P(c|x) \quad (5)$$

Here $\hat{c}$ indicates the final predicted baldness-risk class, and the term $P(c|x)$ implies the predicted probability corresponding to class c for the input risk-factor vector.

AdaBelief Optimization

Adaptive optimizers such as Adam converge faster

than stochastic gradient descent (SGD), but their generalization and stability may not be sufficient for large datasets. AdaBelief introduces a variation of the Adam optimizer to enhance learning stability and model robustness [12]. It determines the magnitude of weight updates based on the concept of 'belief'. In this optimizer, unlike Adam, a novel feature is that s_t represents the exponential moving average of $(g_t - m_t)^2$, while $g_t - m_t$ denotes the gradient deviation. Let it be considered that m_t implies the gradient prediction, and the inverse square root of s_t , $1/\sqrt{s_t}$, denotes the belief in the method.

Explainability Analysis using SHAP

SHAP (SHapley Additive exPlanations) was employed to analyze the contribution of each risk factor to the model prediction, improving model interpretability for baldness risk prediction [13]. This is specifically suitable for baldness risk prediction because various factors may impact the final prediction and may differ from one individual to another. SHAP enables the identification of factors that robustly affect the model outcome and determines whether their contribution increases or decreases the predicted risk of baldness.

Results

The proposed model is simulated using Python 3.6.5 on a PC with an i5-8600k, GeForce 1050Ti 4GB, 16GB RAM, a 250GB SSD, and a 1TB HDD. The parameter settings are given as follows: learning rate: 0.01, dropout: 0.5, batch size: 5, epoch count: 50, and activation: ReLU. To empirically evaluate the XRB-NODE framework, it is tested on the Baldness Risk Factor Dataset [14].

Figure 3 displays the variables and their correlations. The strong red and weak blue represent strong and weak correlations, respectively. It indicates that there are many relationships among variables and factors, such as stress, medical conditions, age, medication, smoking, and environment, suggesting that hair loss may not result from a single factor alone.

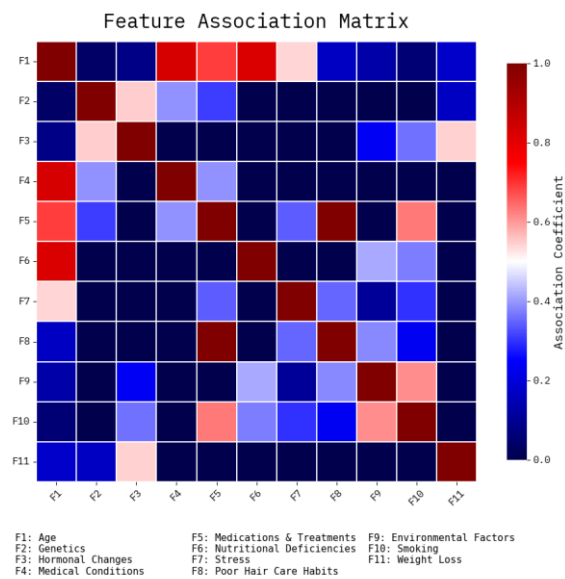


Figure 3. Feature association matrix of factors related to hair loss.

Figure 4 shows how the baldness rate varies across different age groups. The rate is 51.3% for individuals aged 20 years or below and gradually increases to 66.7% in the 31–40 age group. A slight decrease to 64.5% is observed among those aged 41–50 years, followed by the highest rate of 67.2% in the 51–60 age

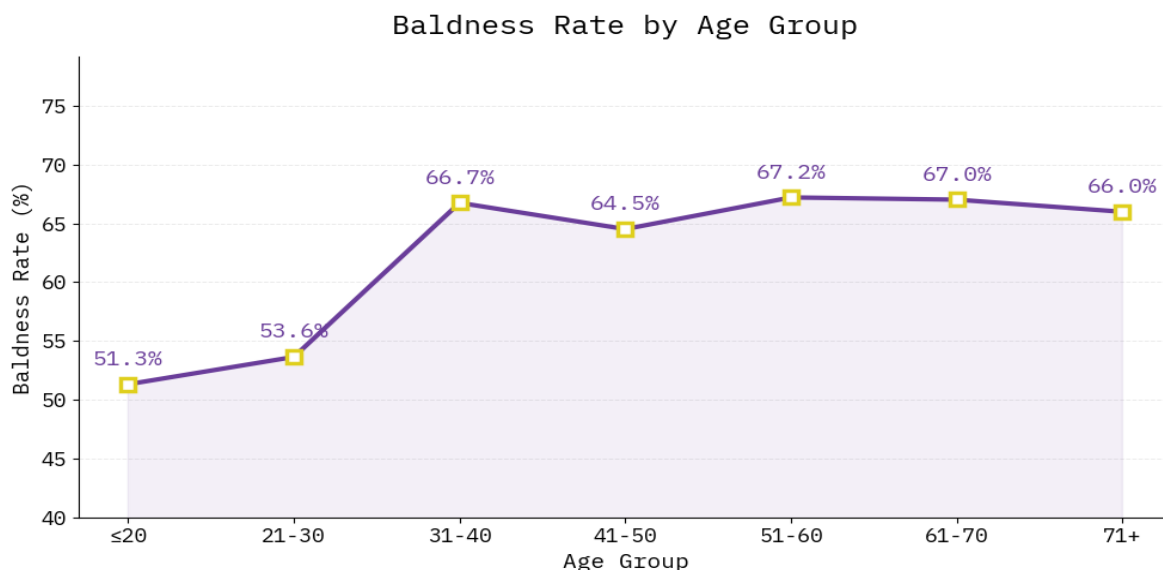


Figure 4. Baldness rate across different age groups.

group. For individuals aged 60 and above, the rate remains fairly stable at 67.0% for the 61–70 age group and 66.0% for those aged 71 and above.

Figure 5 shows baldness rates across multiple stress levels, with and without hormonal variations. Individuals with hormonal changes depict higher baldness rates at all stress levels. The highest rate is recorded under high stress with hormonal changes (94.9%), whereas the lowest rate is observed under medium stress without hormonal changes (49.4%). This demonstrates a stronger correlation with the occurrence of baldness than with stress level.

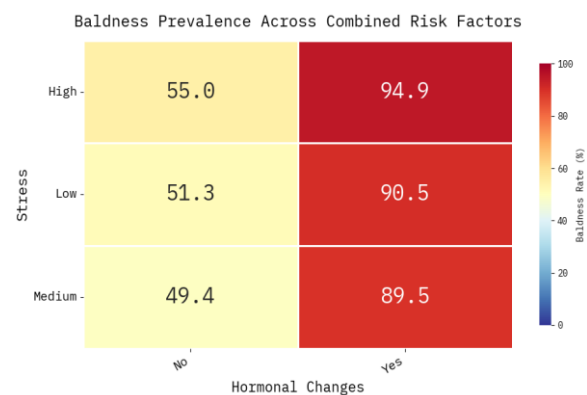


Figure 5. Baldness prevalence across stress levels and hormonal changes.

Table 1 and Figure 6 show the baldness classification results of the XRB-NODE framework using a 70:30 train-test split. The proposed XRB-NODE method achieves average accuracies of 95.06% and 94.20% on the training and testing sets, and MCC

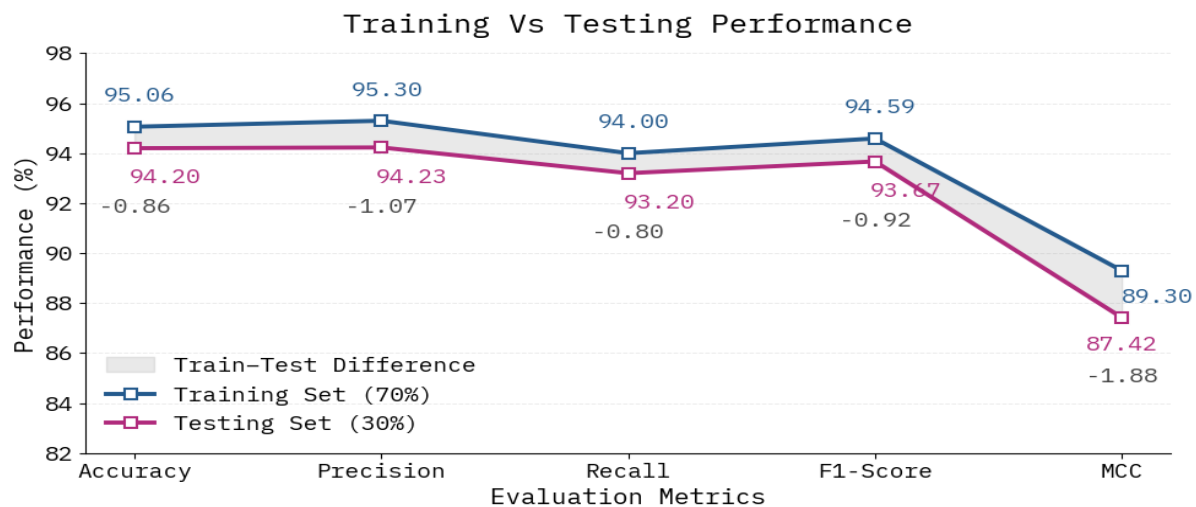


Figure 6. Training and testing performance of the XRB-NODE system with 70:30.

values of 89.30% and 87.42%, respectively, indicating reliable classification of baldness.

Table 1. Baldness classification of XRB-NODE technique on 70:30.

Classes	Accuracy	Precision	Recall	F1-Score	MCC
Training Set (70%)	95.06	95.30	94.00	94.59	89.30
Testing Set (30%)	94.20	94.23	93.20	93.67	87.42

Discussion

Figure 7 presents a comparative assessment of the XRB-NODE system against various measures [15, 16]. The XRB-NODE framework has achieved higher performance, with an accuracy of 95.06%, precision of 95.30%, recall of 94.00%, and an F1-Score of 94.59%. The SVM [16] and LR [16] models performed worse. Additionally, XGBoost [15], CBAM [16], CNN [16], and LightGBM [15] achieved marginally better results than existing approaches. Also, ANN [16] models achieved considerably higher outcomes, with an accuracy of 94.00%, compared with the proposed methods.

Figure 8 exemplifies the plot contribution of different risk factors to the baldness prediction model. Genetics has the maximum overall importance, followed by hormonal variations and medical conditions. Age and medications or treatments also contribute remarkably to the prediction. The remaining features have comparatively smaller impacts, resulting

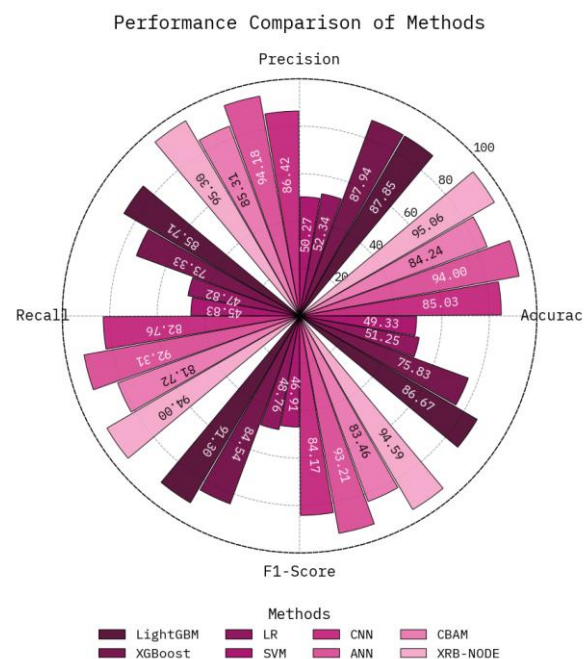


Figure 7. Performance comparison of the XRB-NODE system with several metrics.

in lower overall influence on the model output.

The ablation analysis results are presented in Figure 9 to assess the contribution of each element of the proposed XRB-NODE framework. The baseline NODE method achieved an accuracy of 89.84%. With the integration of the AdaBelief optimizer, performance improved, achieving an accuracy of 91.63% and an F1-score of 89.78%. An additional improvement was observed when Improved ReliefF was incorporated with NODE, resulting in an accuracy

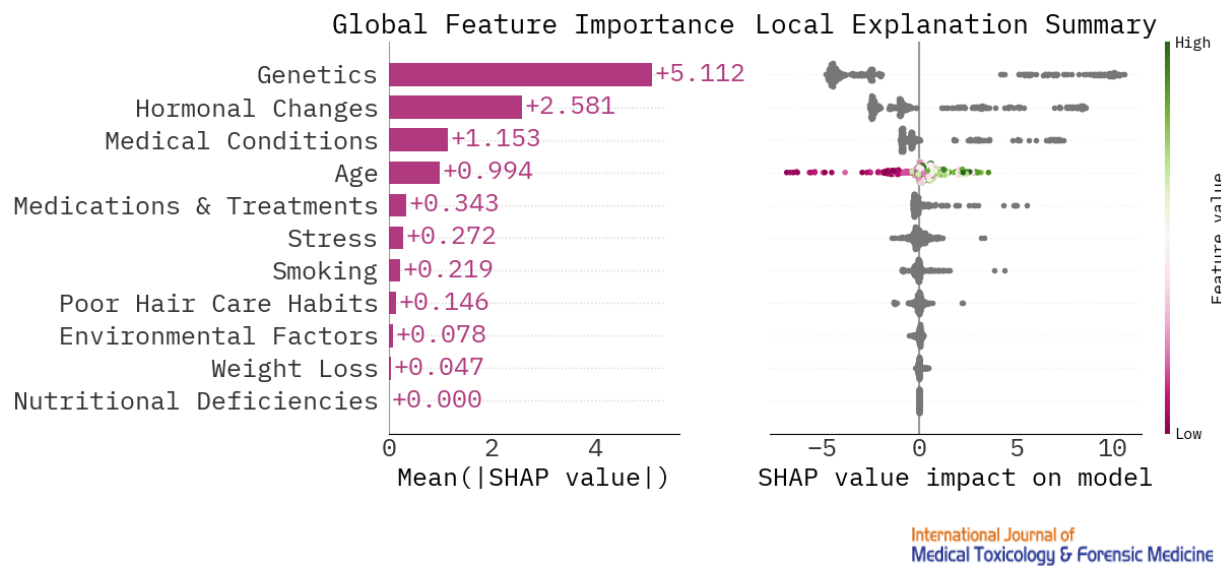


Figure 8. Global feature importance and local SHAP explanation for baldness risk prediction.

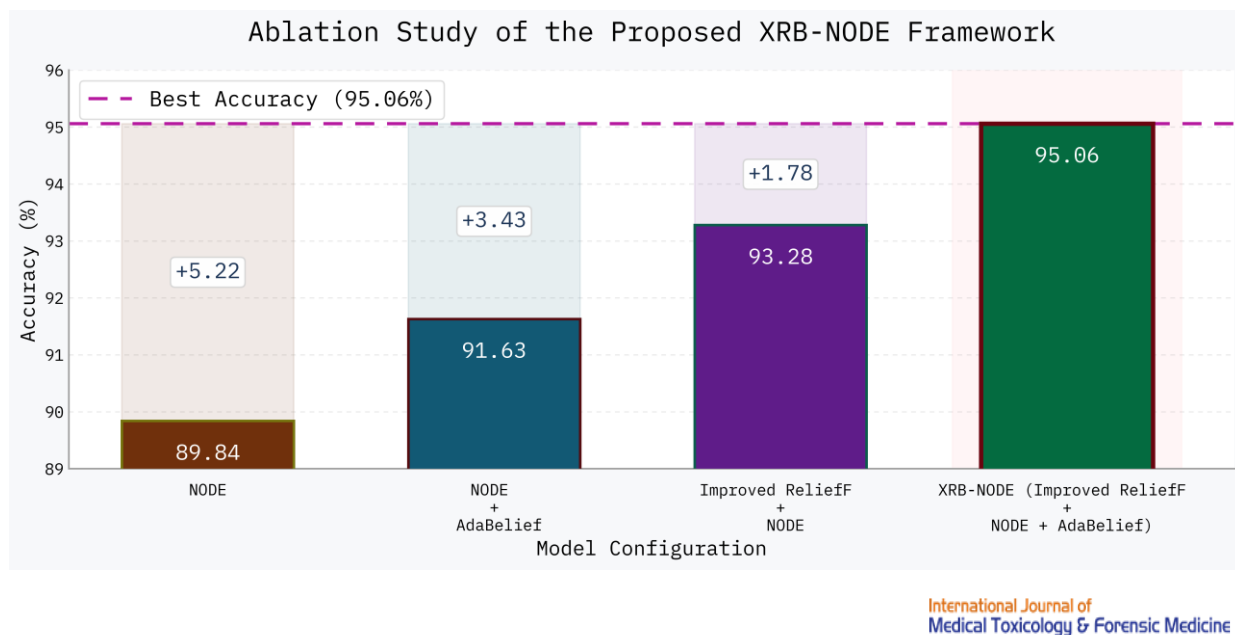


Figure 9. Ablation study of the XRB-NODE methodology using accuracy.

of 93.28%. The XRB-NODE (Improved ReliefF + NODE + AdaBelief) framework achieved the highest performance across all evaluation metrics, with 95.06% accuracy, 95.30% precision, 94.00% recall, and 94.59% F1-score, underscoring the importance of integrating these parameters for improved performance.

The proposed XRB-NODE framework is implemented to predict baldness from a set of significant risk factors. The preprocessing phase also handles missing values, duplicate records, categorical variables, and feature-scale variance before model training. Improved ReliefF selects the risk factors most strongly associated with the prediction, enabling NODE to perform with a more meaningful, smaller feature set. AdaBelief is used for model optimization,

while SHAP-based explanations show how individual risk factors affect the final prediction.

Conclusion

This research has developed an XRB-NODE framework based on different risk factors. The proposed model employs an improved ReliefF method to identify the most relevant factors associated with baldness classification. Moreover, the NODE model categorizes individuals by their risk of baldness. The model is trained using the AdaBelief optimizer to improve learning performance. Additionally, SHAP is used to explain the model's predictions by showing how individual risk factors contribute to the predicted baldness classes. The proposed model is evaluated using the Baldness Risk Factor Dataset, achieving

95.06% accuracy compared with existing methodologies. The proposed model offers a clear and interpretable approach to assessing baldness risk based on relevant risk factors. Future investigations can analyze XRB-NODE's performance using larger datasets that cover diverse age groups and populations.

Ethical Approval

Not applicable.

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Conflicts of Interest

The authors report there are no competing interests to declare.

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