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Research Paper

PEDL-XAI: A Hybrid Probabilistic Ensemble Deep Learning Approach for Hair Disorder Diagnosis

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Abstract

The growing occurrence of hair-related disorders, influenced by modern lifestyles, environmental conditions, and various health issues, has increased the need for intelligent and data-driven healthcare solutions. Conventional methods of hair loss analysis, which rely largely on clinical observation and generalized medical knowledge, often lack precision and fail to account for the combined effects of multiple contributing factors such as genetics, stress, nutrition, and medical history. These limitations underscore the need for advanced systems capable of analysing complex, multi-dimensional data to deliver accurate and reliable predictions. To address this challenge, this study presents an Explainable Artificial Intelligence (XAI)-based hair health prediction system developed using the Flask web framework. The proposed system incorporates data preprocessing, exploratory data analysis, and multiple machine learning algorithms, including Support Vector Machine (SVM), Logistic Regression (LR), Decision Tree (DT), K-Nearest Neighbors (KNN), Gradient Boosting (GB), and AdaBoost (AB). Furthermore, a novel hybrid Probabilistic Ensemble Deep Learning (PEDL) model is introduced, which integrates a Probabilistic Neural Network (PNN) with a Sparse Representation Classifier (SRC) to enhance predictive accuracy. Experimental results demonstrate that the PEDL model achieves a superior accuracy of 0.9950, outperforming conventional machine learning approaches. A significant contribution of this work lies in the integration of XAI techniques, which provide transparent and interpretable predictions by identifying key contributing factors, assessing risk levels, and generating personalized recommendations. The system supports multi-target prediction, including hair loss evaluation, treatment recommendations, and hormonal impact analysis.

Keywords: Explainable Artificial Intelligence (XAI), Hair Health Prediction, Probabilistic Ensemble Deep Learning (PEDL), Machine Learning, Sparse Representation Classifier (SRC), Predictive Healthcare Systems

1. Introduction

Scalp and hair disorders are becoming increasingly common, largely due to elevated stress levels, poor dietary habits, and prolonged exposure to adverse environmental conditions. Typical symptoms include dryness, excessive oiliness, erythema, folliculitis, and dandruff, which, if not properly managed, can develop into inflammatory scalp diseases and significant hair loss [1]. Beyond physical appearance, these conditions can negatively influence an individual's self-esteem, social engagement, and overall quality of life. Therefore, early detection and appropriate intervention are crucial to preventing long-term complications and promoting overall well-being [2]. Furthermore, the global scalp and hair care market, which was valued at USD 91.60 billion in 2022, is projected to experience consistent growth, highlighting the increasing demand for advanced and effective hair healthcare solutions. The conventional approach to diagnosing scalp and hair disorders primarily depends on manual examination performed by dermatologists or trained professionals. This process involves visual inspection and subjective evaluation, as illustrated in Figure 1, and may vary significantly based on the practitioner's experience and expertise. Such methods are often time-consuming, labour-intensive, and require patients to visit specialized clinics for consultation [3]. Additionally, diagnostic accuracy can differ among experts, leading to inconsistencies in treatment recommendations. The approach also demands extensive training and significant educational investment, limiting its accessibility and scalability for large populations.

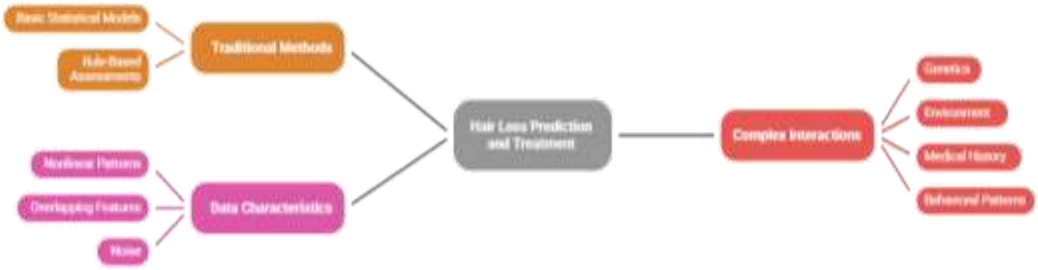

Figure. 1: Factors affecting hair loss prediction accuracy

In recent years, there has been a growing emphasis on developing advanced technological solutions to enhance the efficiency and reliability of scalp and hair disorder analysis [4]. Numerous studies have explored computational techniques for detecting scalp conditions, identifying affected regions, and evaluating severity levels. These approaches aim to reduce reliance on manual assessments while ensuring more consistent and accurate outcomes. However, many existing methods are limited in their ability to simultaneously analyse multiple symptoms and determine both severity and affected areas within a unified framework. This underscores the need for more comprehensive and integrated systems capable of addressing the inherent complexity of scalp and hair disorder diagnosis [5].

2. Literature Survey

Ahmad, et al. [6] Investigated the promising role of machine learning (ML) in the early detection and determination of hair loss, clearing the way for personalized medicines. In order to arrive at a particular outcome, the research incorporates a few techniques, including Random Forest (RF), Support Vector Machine (SVM), as well as KNN. Important elements like feature engineering, preprocessing, and hyperparameter tweaking are used. Traditional approaches are outrun by the outcomes reached, and there is a clear difference when it comes to the accuracy and precision. This study shows the potential of automatic diagnostics that could transform the treatment of hair loss to the enormous benefit of the many afflicted by it.

Ha, et al. [7] Presented an intelligent healthcare platform for identifying severity levels of six common scalp hair disorders such as dryness, oiliness, erythema, folliculitis, dandruff, and hair loss. To establish a suitable scalp image classification model, they tested three deep learning models (ResNet-152, EfficientNet-B6, and ViT-B/16). Among the three tested deep learning models, the ViT-B/16 model exhibited the best classification performance with an average accuracy of 78.31%. In addition, the attention rollout method was applied to explain the decision of the trained ViT-B/16 model and highlight approximate lesion areas with no additional annotation procedure. Finally, Scalp checker software was developed based on the trained ViT-B/16 model and the attention rollout method. Accordingly, this proposed platform facilitates objective monitoring states of the scalp and early diagnosis of hairy scalp problems. Kim, ET AL. [8] proposed an efficient and accurate algorithm to classify hair follicles and estimate hair loss severity, which was implemented and validated using a multitask deep learning method via a Mask R-CNN framework. A microscopic image of the scalp was resized, augmented, then processed through pre-trained ResNet models for feature extraction. The key features considered in this study concerning hair loss severity include the number of hair follicles, the thickness of the hair, and the number of hairs in each hair follicle. Based on these key features, labelling of hair follicles were performed on the images collected from 10 men in varying stages of hair loss. More specifically, Mask R-CNN was applied for instance segmentation of the hair follicle region and to classify the hair follicle state into three categories, following the labelling convention.

Austin, et al. [9] Developed non-invasive ASD biomarkers using mass spectrometry analyses of elemental metabolism in single hair strands, coupled with machine learning. They undertook a national prospective study in Japan, where hair samples were collected at 1 month and clinical diagnosis was undertaken at 4 years. Next, they analyzed a national sample of Swedish twins and, in third study, participants from a specialist ASD center in the US. In a blinded analysis, a predictive algorithm detected ASD risk as early as 1 month with 96.4% sensitivity, 75.4% specificity, and 81.4% accuracy (n = 486; 175 cases). These findings emphasize that the dynamics in elemental metabolism are systemically dysregulated in autism, and these signatures can be detected and leveraged in hair samples to predict the emergence of ASD as early as 1 month of age. Kim M., et al. [10] Gained significant traction in medical image analysis, demonstrating exceptional performance across a wide range of clinical imaging modalities, including X-ray, computed tomography, magnetic resonance imaging, and pathological tissue imaging. As these technologies continue to advance, their applications have rapidly expanded into specialized healthcare areas, such as hair-loss diagnosis and treatment. Hair Density Measurement (HDM), a critical procedure for assessing the severity of hair loss and determining suitability for transplantation, involves counting hair follicles in the occipital donor region—a task well-suited to object detection and classification techniques. To explore the potential of automating HDM, researchers have applied deep learning–based object detection models to evaluate prediction accuracy and feasibility. In one study, a dataset of 4,492 enlarged RGB scalp images from male hair-loss patients, along with detailed annotation data identifying follicle locations and follicle types, was used to train and assess model performance.

Hwang, et al. [11] Proposed a novel generative adversarial network-based ROI image translation method, which converts only the ROI and retains the image for the non-ROI. Specifically, by performing image translation and image segmentation independently, the proposed method generates predictive images from the distribution of images after hair transplant surgery and specifies the ROI to be used for generated images. In addition, by applying the ensemble method to image segmentation, they propose a more robust method through complementing the shortages of various image segmentation models. Igarashi, et al. [12] Investigated the association between GD and thyroid hormone levels in women's hair and evaluated the prediction accuracy of this non-invasive type of sample. By optimizing pretreatment and analysis techniques using liquid chromatography–mass spectrometry (LC-MS), free triiodothyronine (FT3) and thyroxine (FT4) could be detected in only 2 mg of hair with high sensitivity. Compared with healthy controls, the thyroid hormone levels in the hair of GD patients were significantly higher in correlation with blood levels. The predictive ability of hair thyroid hormones was analyzed using a receiver operating characteristic (ROC) curve, and the optimal cut-off value was determined via the Youden index. As a result, the area under the curve (AUC) was 0.974 (95% confidence interval (CI): 0.935–1.000) for FT3 and 0.900 (95% CI: 0.807–0.993) for FT4. The cut-off value was 0.133 pg/mg (sensitivity: 91.2%; specificity: 100%; positive predictive value (PPV): 100%; negative predictive value (NPV): 76.9%) for FT3 and 0.067 pg/mg (sensitivity: 70.6%; specificity: 100%; PPV: 100%; NPV: 50.0%) for FT4.

P. Duraisamy, et al. [13] Explored the effectiveness of various machine learning algorithms in forecasting hair health using a comprehensive dataset incorporating individual traits and lifestyle elements. LR, random forest, and AB were assessed, with random forest notably achieving a remarkable 94.6% accuracy. These results emphasize machine learning's potential for precise, non-invasive personalized hair health predictions. Key factors such as genetics, diet, and stress were pinpointed, informing targeted care approaches. The research underscores machine learning's promise in accurately anticipating hair loss and suggests future avenues for expanding datasets, integrating diverse data sources, and developing user-friendly tools for improved hair care management. Jin, et al. [14] Allowed users to easily diagnose the condition of their scalp was also proposed. The results showed that the accuracy of the diagnosis model for fine dandruff and perifollicular erythema was 75% and 82%, respectively. It showed good performance in classifying normal, mild, moderate, and severe cases compared to previous studies. Finally, a fast and convenient web platform was developed where users can upload an image and immediately visualize their scalp condition, receive diagnostic results, and see similar cases and solutions. The analysis of user satisfaction indicates that this web application has achieved exceptional outcomes in terms of user satisfaction, garnering high evaluations for its usability, design effectiveness, and overall user experience. This setup enables users to easily check their scalp condition and is accessible to everyone, which is a significant advantage. This is expected to play a crucial role in contributing to global scalp health by advocating the benefits of the early detection and treatment of scalp-related conditions.

Nagase, et al. [15] Reviewed based on hair structures from macroscopic to microscopic viewpoints. Hair appearance is the result of optical events, such as reflection, refraction, scattering, and absorption. The effects of hair structures on such optical events are summarized and structural conditions for hair appearance are considered. Hair structures are classified into the following: the alignment of multiple hair fibres, the cross-sectional shape of the hair fiber, and the microstructures of hair fibre (cuticle, cortex, and medulla). The alignment of multiple hair fibres is easily affected by the existence of meandering fibers and their alignment along hair length becomes less synchronized. The less-synchronized orientation of multiple fibers causes the broadening of the apparent reflection and luster-less dull impression. The cross-sectional shape of hair fiber affects light reflection behaviour. Hair fibers with elliptical cross-section show glittering coloured light based on total reflection in the hair. The scaly structures of cuticles at the surface of hair are often uplifted and cause light scattering and then affect hair luster.

3. Proposed System

The proposed methodology presents a structured and data-driven approach for analysing factors that influence hair health and generating reliable predictions. It follows a systematic pipeline that begins with data collection, preprocessing, and feature encoding, ensuring that both categorical and numerical inputs are transformed into a consistent format suitable for analysis. Multiple classical machine learning models are incorporated to evaluate different learning behaviours, while a hybrid deep learning and ensemble-based classifier is introduced to improve predictive performance and adaptability, as shown in figure 2. A lightweight database system is used to manage user information, prediction records, and model outputs efficiently, while a web-based interface enables seamless interaction, visualization, and real-time prediction generation. The methodology also supports model retraining, allowing continuous improvement in performance as new data becomes available.

User Interface (Web Browser)

- The user interacts with the system through a browser-based interface.
- It allows functionalities such as user registration, login, data input, prediction requests, EDA visualization, and model training.
- The interface sends user inputs as HTTP requests to the backend server.

Flask Web Server (app.py)

- The backend server handles all incoming requests and routes them to appropriate modules.
- It manages authentication, prediction workflows, EDA visualization, and model training processes.
- The server acts as a bridge between the user interface, database, and machine learning models.
- It also controls model loading and execution for real-time predictions.

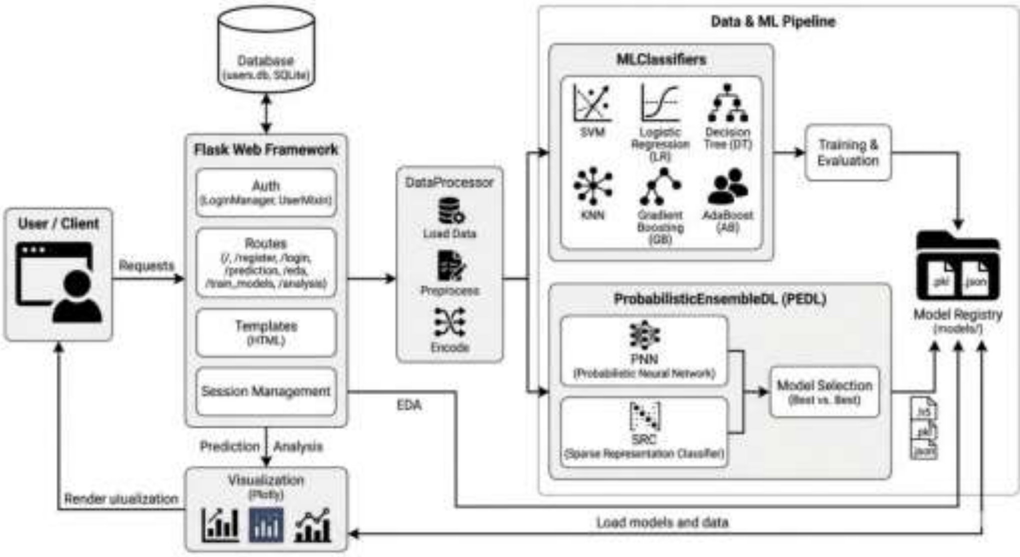

Figure. 2: Proposed system architecture

SQLite Database (users.db)

- The database stores user registration details and login credentials securely.
- It ensures persistent storage of user-related information required for authentication.
- The Flask server interacts with the database for retrieving and storing user data.

Raw Dataset (CSV Input)

- The dataset serves as the primary input source containing various features affecting hair health.
- It includes attributes such as genetics, stress levels, medical conditions, nutritional deficiencies, age, environmental factors, smoking habits, and weight loss.
- This raw data is passed to the preprocessing module for further transformation.

Data Preprocessing & Feature Encoding (DataProcessor.py)

- The dataset undergoes cleaning, transformation, and encoding before model training.
- Categorical features are converted into numerical form using label encoding.
- Feature columns are separated from target variables to prepare input-output pairs.
- The processed data is standardized and forwarded to machine learning models.

Existing Machine Learning Models (SVM, LR, DT, KNN, GB, AB)

The processed feature set is provided to multiple baseline models for comparative analysis:

- **SVM:** For nonlinear classification.
- **LR:** For linear decision boundaries.
- **DT:** For rule-based classification.
- **KNN:** For distance-based learning.
- **GB:** For improved accuracy through boosting.
- **AB:** For adaptive error correction.

Each model generates predictions for three target variables: Hair Loss, Medications & Treatments, and Hormonal Changes.

Proposed Hybrid PEDP Model (PNN with SRC)

This is the core intelligent fusion model of the system, consisting of two distinct components:

1. **PNN:** Processes input features through multiple dense layers to capture complex nonlinear relationships and produce probability-based predictions.
2. **SRC:** Uses sparse data representation to generate interpretable predictions based on specific feature contributions.

Selection Logic (Best Model Selection)

- The framework evaluates the performance of the PNN and SRC using specific evaluation metrics.
- The model with the highest accuracy is dynamically selected as the Final Prediction Model.
- This "best-of" approach ensures maximum reliability and adaptability across different data distributions.

Prediction Results & Target Output

- The system generates outputs for the three primary targets: Hair Loss, Medications & Treatments, and Hormonal Changes.
- Results are displayed on the user interface in an understandable format, including class labels and comparative insights across the different models.

Model Training & Retraining Module

- The system allows for manual training of models through user-triggered actions in the UI.
- Updated datasets can be used to retrain the pipeline, after which performance metrics are recalculated and stored.
- This adaptive learning cycle ensures the system maintains long-term accuracy as new hair health data becomes available.

4. Results Description

The results demonstrate the effectiveness of the developed system in analysing input features and generating accurate predictions across multiple target variables. Various machine learning models such as SVM, LR, DT, KNN, GB, AB, and the hybrid PEDP were evaluated using standard performance metrics. The comparative analysis highlights the ability of the models to capture patterns and relationships within the dataset. The hybrid PEDP model shows improved performance by combining deep learning and rule-based classification techniques. Visualization tools further support the interpretation of results by presenting clear insights into model behaviour and data patterns. The system successfully delivers consistent and reliable outputs for real-time prediction scenarios.

Figure 3 illustrates the Accuracy Comparison Across All Targets, providing a unified visualization of how various machine learning models perform for the three prediction categories: Hair Loss, Medications & Treatments, and Hormonal Changes. The bar chart compares the accuracy of models such as SVM, LR, DT, KNN, GB, AB, and the PEDL model. The results clearly show that the Probabilistic Ensemble DL model consistently achieves the highest accuracy across all targets, highlighting its superior capability in capturing complex patterns within the dataset. Models like KNN and GB also perform reasonably well, while traditional models demonstrate moderate accuracy.

Figure. 3: Performance comparison across all Targets

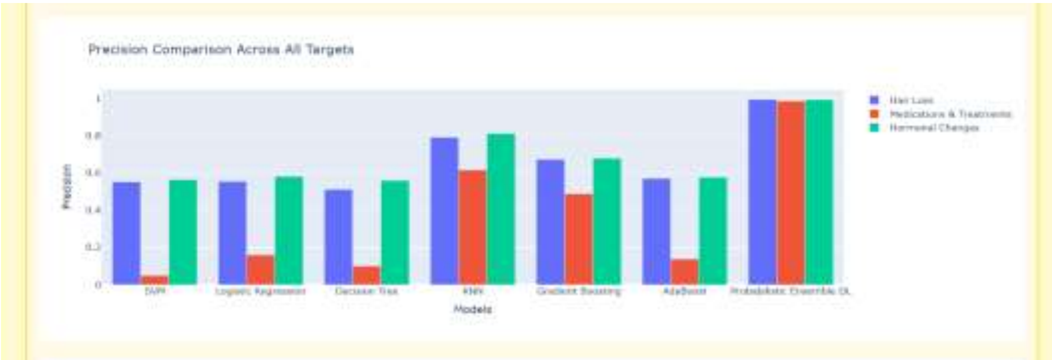

Figure. 4: Precision comparison across all targets

Figure 4 illustrates the Precision Comparison Across All Targets, showing how different machine learning models perform in terms of precision for the three prediction categories: Hair Loss, Medications & Treatments, and Hormonal Changes. The chart compares models such as SVM, LR, DT, KNN, GB, AB, and the PEDL model. The visualization highlights that the Probabilistic Ensemble DL model consistently achieves the highest precision across all targets, demonstrating its ability to make highly accurate positive predictions. KNN and GB also show relatively strong precision scores, while traditional models like SVM and LR perform moderately depending on the target. This comparison provides valuable insights into the reliability of each model when predicting positive cases across different clinical and lifestyle factors.

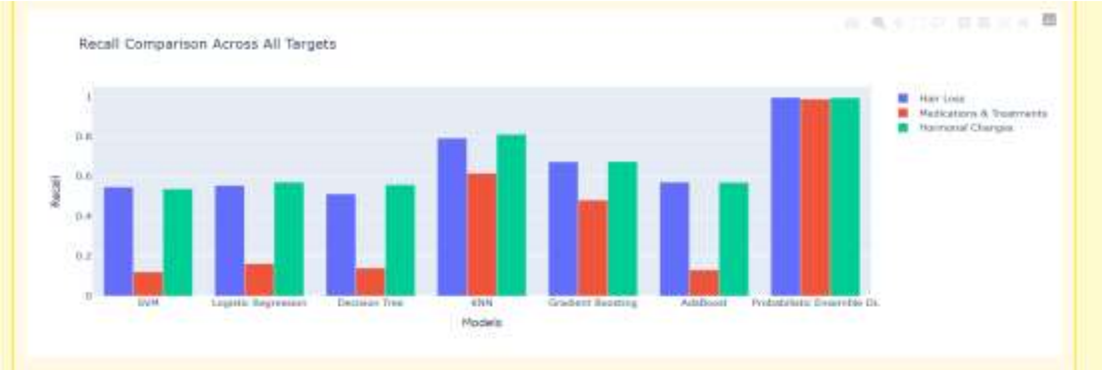

Figure. 5: Recall comparison across all targets

Figure 5 illustrates the Recall Comparison Across All Targets, comparing how effectively different machine learning models identify actual positive cases for Hair Loss, Medications & Treatments, and Hormonal Changes. The bar chart evaluates models such as SVM, LR, DT, KNN, GB, AB, and the PEDL model. The results show that the Probabilistic Ensemble DL model consistently achieves the highest recall across all target variables, indicating its strong ability to minimize false negatives. KNN and GB also perform well, particularly for Hormonal Changes and Hair Loss, while models like SVM and LR exhibit moderate recall performance. This figure provides valuable insight into each model's sensitivity and highlights which models are most reliable when identifying true positive cases across multiple prediction tasks.

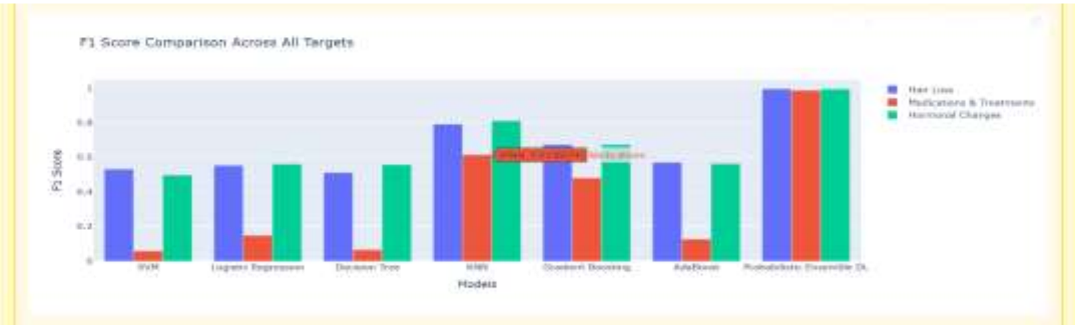

Figure. 6: F1-score comparison across all targets

Figure 6 illustrates the F1-Score Comparison Across All Targets, providing a combined view of how different machine learning models balance precision and recall for predicting Hair Loss, Medications & Treatments, and Hormonal Changes. The bar chart compares the F1-scores of models including SVM, LR, DT, KNN, GB, AB, and the PEDL model. Like the previous metrics, the Probabilistic Ensemble DL model consistently achieves the highest F1-scores across all target variables, indicating its strong overall predictive capability. KNN and GB also deliver competitive performance, especially for Hormonal Changes and Hair Loss, while traditional models show moderate results. This figure offers a comprehensive insight into each model's effectiveness, making it valuable for selecting the most balanced and reliable classifier for the prediction system.

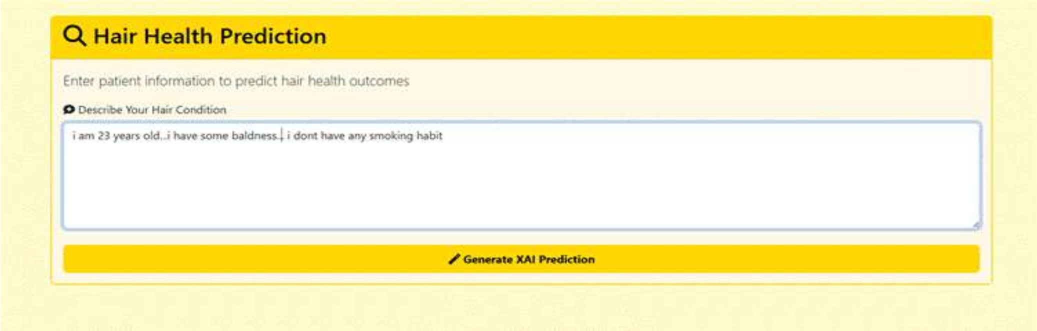

Figure. 7: Hair health XAI prediction

Figure 7 illustrates the Hair Health Prediction interface where user-provided inputs regarding personal hair condition are utilized to generate an explainable AI-based prediction. The system captures descriptive information such as age, lifestyle habits, and observed symptoms to assess hair health status. It emphasizes user-driven input for personalized analysis, enabling the model to interpret real-world conditions effectively. The interface supports the initiation of prediction generation through an integrated mechanism that triggers the underlying machine learning model.

Figure 8 depicts the detailed XAI-based prediction report generated by the system, presenting a structured clinical-style analysis of hair loss risk. It includes probability estimation, severity level, and a concise explanation derived from the model's interpretation of input features. The report further identifies key contributing factors such as genetics, stress, diet, and lifestyle influences affecting hair health. It provides recommended treatments and preventive measures based on predicted outcomes, ensuring actionable insights.

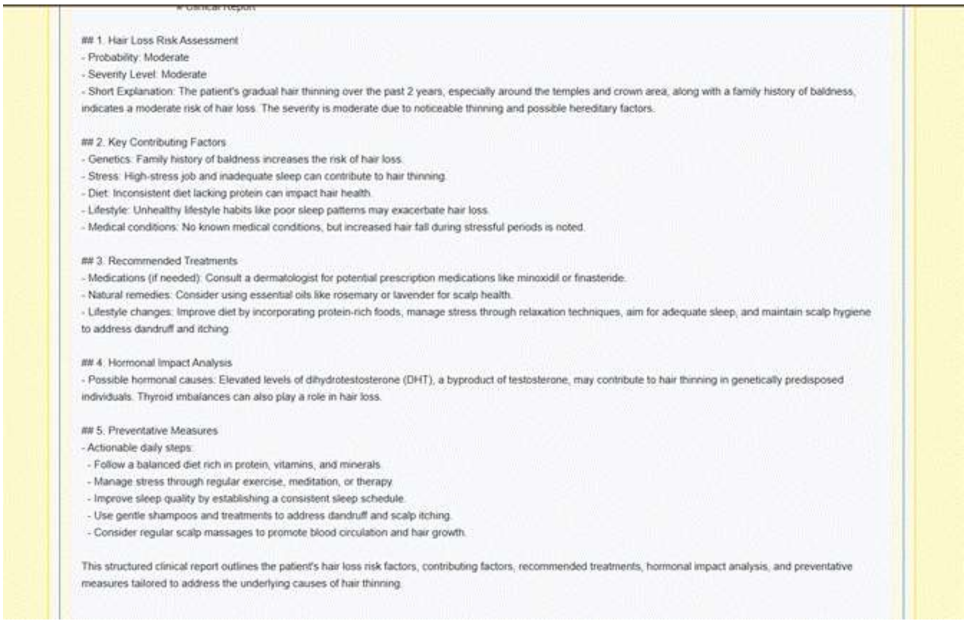

Figure. 8: Detailed XAI prediction report

Table. 1: Comparative analysis of classification models for hair loss prediction

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.5463	0.5515	0.5463	0.5310
LR	0.5537	0.5546	0.5537	0.5529

DT	0.5112	0.5115	0.5112	0.5109
KNN	0.7913	0.7916	0.7913	0.7912
GB	0.6725	0.6726	0.6725	0.6725
AB	0.5700	0.5704	0.5700	0.5698
PEDL	0.9950	0.9950	0.9950	0.9950

Table. 2: Comparative analysis of classification models for medications & treatments prediction

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.1200	0.0486	0.1200	0.0587
LR	0.1613	0.1591	0.1613	0.1479
DT	0.1400	0.0999	0.1400	0.0654
KNN	0.6150	0.6161	0.6150	0.6137
GB	0.4800	0.4883	0.4800	0.4802
AB	0.1300	0.1372	0.1300	0.1266
PEDL	0.9862	0.9865	0.9862	0.9862

The comparative analysis of different models clearly table 1 shows significant variation in performance across all evaluation metrics. Among the classical models, KNN achieves the highest accuracy of 0.7913 along with strong precision, recall, and F1-score values, indicating its effectiveness in capturing data patterns. GB follows with an accuracy of 0.6725, providing moderate performance, while LR and AB show relatively lower accuracies of 0.5537 and 0.5700 respectively. SVM records an accuracy of 0.5463, and DT performs the lowest with an accuracy of 0.5112, reflecting limited predictive capability. In contrast, the proposed PEDL model significantly outperforms all other models with an accuracy of 0.9950 and equally high precision, recall, and F1-score values. This demonstrates the strength of combining PNN and SRC in a hybrid framework, enabling superior learning and generalization.

The comparative analysis for table 2 highlights noticeable differences in model performance across all evaluation metrics. Among the traditional models, KNN achieves the highest accuracy of 0.6150 along with balanced precision, recall, and F1-score, making it the most effective among classical approaches. GB follows with an accuracy of 0.4800, showing moderate performance, while LR records an accuracy of 0.1613 with relatively lower predictive capability. DT and AB perform poorly with accuracies of 0.1400 and 0.1300 respectively, indicating limited learning efficiency. SVM shows the lowest performance with an accuracy of 0.1200 and weak precision and F1-score values. In contrast, the proposed PEDL model significantly outperforms all other models with an accuracy of 0.9862 and consistently high precision, recall, and F1-score values. This demonstrates the effectiveness of the hybrid approach combining PNN and SRC in capturing complex relationships within the data.

Table. 3: Comparative analysis of classification models for hormonal changes prediction

Model	Accuracy	Precision	Recall	F1-Score
SVM	0.5363	0.5636	0.5363	0.4964

LR	0.5700	0.5809	0.5700	0.5607
DT	0.5575	0.5593	0.5575	0.5567
KNN	0.8100	0.8114	0.8100	0.8100
GB	0.6737	0.6781	0.6737	0.6727
AB	0.5687	0.5762	0.5687	0.5628
PEDL	0.9938	0.9938	0.9938	0.9938

The comparative analysis of table 3 or hormonal changes prediction shows clear differences in model performance across all evaluation metrics. Among the classical models, KNN achieves the highest accuracy of 0.8100 along with strong precision, recall, and F1-score values, indicating its effectiveness in capturing patterns in the dataset. GB follows with an accuracy of 0.6737, providing moderate performance, while LR and AB record accuracies of 0.5700 and 0.5687 respectively. DT shows slightly lower performance with an accuracy of 0.5575, and SVM achieves an accuracy of 0.5363, indicating comparatively weaker results. Despite these variations, all traditional models perform significantly lower than the proposed hybrid approach. The PEDL model outperforms all others with an accuracy of 0.9938 and equally high precision, recall, and F1-score values. This highlights the strength of combining PNN and SRC in handling complex feature relationships.

5. Conclusion

The study successfully demonstrates the effectiveness of a data-driven approach for analysing factors related to hair health and generating accurate predictions across multiple target variables. The integration of data preprocessing, exploratory analysis, and multiple machine learning models ensures a structured and reliable workflow. Among the classical models, KNN consistently shows better performance compared to others, while models like SVM and DT exhibit relatively lower accuracy. The implementation of the hybrid PEDL model significantly improves performance, achieving near-perfect accuracy across all target predictions. This improvement is mainly due to the combination of deep learning capabilities of PNN and the interpretability of SRC. The system effectively handles both categorical and numerical data, ensuring consistency and robustness in predictions. Additionally, the use of evaluation metrics such as accuracy, precision, recall, and F1-score confirms the reliability of the proposed approach.

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