

Enhancing Hairfall Prediction: A Comparative Analysis of Individual Algorithms and An Ensemble Method

Chennu Naga Venkata Sai¹, E. Archana², Bandi Vivek³, Batini Dhanwanth⁴, Viknesh K S⁵

¹Department of Computer Science and Engineering,
K L Deemed to be University,
Green Fields, Vaddeswaram, India - 522302
chennunagavenkatasai@gmail.com

²Department of Computer Science and Engineering,
Panimalar Engineering College,
Chennai, India – 600123
archana.athi@gmail.com

³Department of Computer Science and Engineering,
Panimalar Institute of Technology,
Chennai, India - 600123
vivekbandi03@gmail.com

⁴Department of Computer Science and Engineering,
Panimalar Institute of Technology,
Chennai, India - 600123
dhanwanthbethini01@gmail.com

⁶Department of Computer Science and Engineering,
Panimalar Institute of Technology,
Chennai, India - 600123
vickyviknesh0987@gmail.com

Abstract— Hair fall, a prevalent issue affecting many individuals globally, necessitates early detection for preventive measures and hair health maintenance. Machine learning algorithms have gained attention in predicting hair fall by analysing genetic predisposition, lifestyle habits, and environmental factors. However, the performance of individual algorithms can be improved through ensemble models that combine their strengths. This research paper proposes an ensemble machine learning approach tailored for hair fall prediction. Comparative evaluations with individual algorithms reveal the ensemble models consistently outperform in accuracy, precision, and recall. Leveraging diverse algorithms, the ensemble approach captures a wider range of hair fall patterns, enhancing prediction accuracy. The ensemble models also exhibit higher precision and recall rates, correctly identifying both hair fall and non-hair fall instances. The ensemble models' superiority stems from mitigating the limitations of individual algorithms, resulting in a comprehensive and robust prediction framework. Overall, this research showcases the efficacy of ensemble machine learning models in hair fall prediction, enabling early detection and intervention for hair loss prevention. These findings provide valuable insights for researchers, practitioners, and individuals concerned about hair health.

Keywords- Hair-fall, Machine Learning, Ensemble learning, Accuracy, Precision, Recall.

I. INTRODUCTION

Alopecia, also referred to as hair loss or hair fall, is a widespread condition that affects millions of people worldwide. Numerous factors, including genetics, hormonal imbalances, stress, and dietary deficiencies, can contribute to hair loss. Hair fall can affect a person's self-esteem and confidence, and in severe cases, it can lead to baldness. Therefore, predicting hair fall can help in the early detection and prevention of hair loss. Machine learning algorithms have become increasingly common in hair fall prediction. These algorithms use historical data to learn patterns and make predictions about future hair

fall. The two types of machine learning algorithms are individual algorithms and ensemble techniques. Numerous algorithms, such as decision trees, random forests, support vector machines, and logistic regression, can be independently used to predict hair loss. But by combining them into an ensemble model, individual algorithms' performance can be enhanced. Ensemble methods like bagging, boosting, and stacking combine the predictions of various different individual algorithms in order to increase the precision and robustness of the prediction model.

Ensemble machine learning methods have been utilized in a number of industries including finance, medical, and social media analysis. However, there has been little investigation into the application of ensemble machine learning methods in hair fall prediction. Therefore, in this research paper, an ensemble machine learning method for hair fall prediction. Compare the performance of different individual algorithms and ensemble models using various evaluation metrics. Our goal is to improve hair fall prediction models' robustness and accuracy using ensemble machine learning techniques. The suggested approach can be used as a tool for early hair loss detection and prevention. Early detection of hair loss can assist in prompt action being taken to stop further hair loss. The proposed method can be used by individuals who are concerned about their hair fall, as well as by healthcare professionals who want to monitor their patients' hair health.

The proposed method can also be used by the cosmetic industry to develop personalized hair care products for individuals based on their hair fall prediction. The study focuses on developing a deep learning-based approach to accurately measure hair density, which is an important parameter in various fields including hair transplantation and hair loss research. By comparing their method to manual measurements of hair density, the researchers show that it is effective and that the results are promising with high accuracy and precision. The research paper highlights the potential of deep neural networks in automating hair density measurements, offering a faster and more reliable alternative to manual measurements for various applications in the field of hair research [1]. The research paper by Gupta et al. explores the role of AI in addressing hair-related issues, such as hair loss, transplantation, and disorders like alopecia. The study evaluates the effectiveness of AI-based approaches in diagnosing and treating hair disorders, comparing their accuracy and reliability to traditional methods. The findings highlight the potential of AI to revolutionize the field of hair restoration, offering improved diagnosis, treatment, and patient care. Overall, the research underscores the promising role of AI in advancing the understanding and management of hair-related conditions [2].

II. LITERATURE REVIEW

The research paper by Sayyad and Midhunchakkaravathy focuses on utilizing machine learning techniques to develop a diagnostic model for Alopecia Areata, with the goal of enhancing accuracy and efficiency in diagnosis. Through an investigation of different machine learning algorithms, the authors evaluate their performance in diagnosing Alopecia Areata, shedding light on the potential of machine learning in this field. Overall, the paper offers useful insights into the use of machine learning in Alopecia Areata diagnosis and management, providing opportunities for improved Alopecia

Areata diagnosis and management [3]. The research paper by Kim et al. [4] explores the use of deep learning techniques for accurate hair follicle classification and severity estimation of baldness. They employ Mask R-CNN, cutting-edge object detection and segmentation model, to analyze hair follicles and assess the extent of hair loss. The findings underscore the significance of Mask R-CNN in enhancing the understanding and evaluation of hair loss, providing a valuable resource for dermatologists and specialists in hair restoration. Overall, this research showcases the potential of deep learning in improving diagnoses and treatment strategies for individuals experiencing hair loss.

The research paper by Sayyad et al. [5] introduces a classification model that combines VGG deep learning architecture with SVM for precise classification of Alopecia Areata. Through evaluation on a dataset of Alopecia Areata images, the authors demonstrate the effectiveness of their framework in distinguishing between different subtypes of the condition. The study emphasizes the potential of the VGG-SVM approach in enhancing the classification of Alopecia Areata, enabling more accurate diagnoses and personalized treatment strategies. Overall, this research contributes to improved management and understanding of this hair loss disorder. The research paper by Benhabiles et al. [6] presents an approach using deep learning for automatic analysis of facial images to classify hair loss severity. Their proposed deep learning model demonstrates effective detection and classification of various levels of hair loss, providing a non-invasive and efficient assessment method. The study showcases the potential of deep learning in accurately quantifying and detecting hair loss levels from facial images, contributing to the advancement of computer-assisted tools for hair loss diagnosis and evaluation. Overall, this research offers promising prospects to enhance the precision and efficacy of hair loss evaluations.

The research paper by Chang et al. [7] introduces a mobile device-based system that utilizes deep learning algorithms to analyze scalp images and provide accurate diagnoses for various conditions. The authors successfully demonstrate the effectiveness of their system in diagnosing hair loss, dandruff, and scalp infections, offering individuals a convenient and accessible tool for assessing scalp health. This research emphasizes the potential of mobile device-based systems and deep learning techniques in improving scalp diagnosis, enabling individuals to monitor and manage their scalp conditions more effectively. The research paper by Su et al. [8] introduces an automated system that combines image processing and machine learning techniques to analyze scalp images and provide accurate assessments of scalp health. The authors successfully demonstrate the effectiveness of their

system in detecting and diagnosing various scalp conditions, including dandruff, scalp infections, and hair loss. This research highlights the potential of intelligent systems in improving scalp health diagnosis and personalized care, offering a comprehensive and efficient approach for maintaining optimal scalp conditions.

Kim et al.'s [9] method for precisely identifying and categorizing hair follicles in scalp images makes use of the Mask R-CNN model. The authors provide insightful information for the diagnosis and follow-up of hair loss conditions while successfully demonstrating the efficacy of their approach in estimating the severity of hair loss. Overall, the study shows how advanced computer vision techniques, in particular Mask R-CNN, may enhance hair follicle analysis and hair loss severity estimation, advancing the development of individualized hair restoration treatments. Mrinmoy Roy and Anica Tasnim Protity propose an approach that combines machine learning algorithms and image processing methods for accurate diagnosis of hair and scalp diseases. The methodology demonstrates its effectiveness through experiments and evaluations, successfully detecting and classifying various conditions. The study highlights how machine learning and image processing could improve the detection and treatment of hair and scalp conditions, offering a promising direction for developments in dermatology and trichology [10].

C. Saraswathi and B. Pushpa conduct a comprehensive survey of the application of computer imaging techniques in the detection and analysis of Alopecia Areata and scalp conditions. The authors explore various image processing algorithms and machine learning approaches employed in this domain. The study provides valuable insights into the advancements and challenges associated with computer imaging for diagnosing Alopecia Areata and scalp-related issues. Overall, the research paper contributes to the existing knowledge by summarizing the state-of-the-art techniques and highlighting the potential of computer imaging in improving the diagnosis and management of Alopecia Areata and related scalp conditions [11]. Gregor Urban et al. [12] investigate the applications of laser technology in the field of surgery and medicine. The authors discuss various laser techniques and their effectiveness in diverse medical procedures. The study emphasizes the benefits of lasers, such as their precision, low level of intrusion, and potential for targeted therapies. Overall, the research paper provides valuable insights into the wide-ranging applications of lasers in surgery and medicine, paving the way for advancements in medical technology and patient care. An early alopecia diagnosis method based on machine learning is proposed by Ishita Kapoor and Anju Mishra. The authors create a classification model that successfully compares various features taken from scalp images to identify various alopecia

stages. The study shows how the suggested method accurately and effectively diagnoses alopecia at an early stage, allowing for prompt intervention and treatment. The study, in general, highlights the potential of machine learning techniques in enhancing the diagnosis and management of alopecia, improving patient outcomes and care [13].

Choudhary Sobhan Shakeel et al. [14] propose a machine learning-based framework for distinguishing between healthy hairs and alopecia areata. The authors employ various machine learning algorithms to analyse a dataset of hair images and extract meaningful features. The study demonstrates the effectiveness of the proposed approach in accurately classifying healthy hairs and alopecia areata, providing valuable insights for early detection and diagnosis. Overall, the research paper emphasizes the potential of machine learning techniques in enhancing the classification and understanding of hair conditions, facilitating individualized care and treatment. The authors provide a comprehensive overview of the condition, including its clinical features, pathogenesis, and diagnostic criteria. They discuss the various treatment modalities available for managing FPHL, highlighting the importance of individualized approaches based on the severity and progression of the condition. The study is an invaluable resource for dermatologists and healthcare professionals involved in the diagnosis and treatment of FPHL, aiding in the development of evidence-based strategies for optimal patient care [15]. In their novel approach, the authors extract and compute the features of hair loss using grid line selection and eigenvalue methods. Their approach aims to improve the precision and effectiveness of trichoscopy in identifying and tracking alopecia areata. The study advances dermatology by offering a useful framework for using trichoscopy as a diagnostic method for this particular hair loss condition [16].

III. PROPOSED METHODOLOGY:

A number of steps and techniques are used in the proposed ensemble machine learning method for hair fall prediction to increase the precision and robustness of the prediction model. This section outlines the methodology this study used to develop an ensemble machine learning approach for anticipating hair loss.

The appropriate sensors contributing mother and fetal well-being are integrated into Arduino board to build device layer.

In order to transmit the data from IoT sensory unit to processing, a communication layer is established through a global system for mobile communication (GSM) module compatible to Arduino. For processing the data and predicting the risk, a cloud platform is utilized as processing layer. Mobile applications through which the results are displayed takes role of an application layer. The medical professionals

are enabled to view the result and communicate the same to the patients. The maternal monitoring system is captured in Figure 1.

A. *Data Pre-processing:*

A crucial step in machine learning is data pre-processing, which entails cleaning and converting raw data into a format that can be used for analysis. Collect data on hair fall from a variety of sources, including surveys, online forums, and medical records, in the case of predicting hair loss. The performance of the prediction model can be impacted by the data's potential for missing values, outliers, or inconsistent values. Preparing the data for analysis therefore requires a number of pre-processing steps. Eliminating any invalid or missing values from the data is the first step in the pre-processing of data. To fill in the gaps left by missing values, use methods like mean, median, and mode imputation. Additionally, eliminate any redundant or pointless data that could influence how well the prediction model performs. To find any outliers or anomalies in the data, use data visualization techniques like histograms, scatter plots, and box plots.

Extraction of pertinent features from the data is the following step in the pre-processing of data. Features are the aspects of the data that can be used to make predictions. Take characteristics from the data, such as age, gender, stress level, and nutritional status, and use them to predict hair loss. Additionally, use feature engineering to produce fresh features that could raise the prediction model's accuracy. For instance, you could combine two or more existing features to create a new feature, or you could apply a mathematical transformation like a logarithmic or exponential transformation.

Once the features have been extracted, normalize the data to make sure that they all have the same scale and range. Due to the sensitivity of some machine learning algorithms to the scale of the features, normalization is crucial. To normalize the data, use strategies like robust scaling, z-score scaling, and min-max scaling.

In comparison to the training set, which is used to train machine learning algorithms, the testing set is used to evaluate how well the prediction model performed. The testing set is used to gauge how well the prediction model performed, while the training set is used to train the machine learning algorithms.

B. *Individual Algorithm Training:*

The second stage of our methodology consists of training different machine learning algorithms on the pre-processed data. Utilizing the decision tree, random forest, support vector machine, and logistic regression algorithms, makes specific predictions about hair loss.

A decision tree, a popular machine learning algorithm, makes decisions using a structure that resembles a tree. By dividing the data into smaller subsets based on the values of the features, a tree-like model resembling structure is constructed in order to make predictions. A decision tree extension called random forest uses multiple decision trees to improve the prediction model's accuracy and robustness. Support vector machines, another popular machine learning algorithm, classify data by identifying the best hyper plane before dividing it into different groups.

The statistical technique known as logistic regression models a dependent variable along with one or more independent variables. Utilize the training set to develop each individual algorithm, and the testing set to evaluate its performance. By using techniques like grid search and cross-validation, you can improve the performance of each algorithm by modifying its hyper parameters. In place of learning from the data, hyper parameters are algorithmic parameters that are set by the user.

The decision tree's maximum depth, the random forest's number of trees, and the regularization parameter of the support vector machine are a few examples of hyper parameters that can be changed to improve algorithm performance.

C. *Ensemble Model Training:*

In the final step of our methodology, combine the predictions of the individual algorithms using ensemble methods such as bagging, boosting, and stacking. When bagging, use multiple instances of the same algorithm trained on different subsets of the training data, then combine their predictions using a voting or averaging scheme. When an algorithm's variance but biases are both high, bagging is useful.

In boosting, Train a sequence of weak individual algorithms on the same dataset, where each subsequent algorithm focuses more on the misclassified instances from the previous algorithm. Boosting is useful when the individual algorithms have high bias but low variance. While stacking, Train multiple individual algorithms and combine their predictions using a meta-learner.

The meta-learner builds a new model using the input features from the predictions made by the individual algorithms. Stacking is advantageous when the individual algorithms can complement one another and have varying strengths and weaknesses. Utilize the training set to train the ensemble model and evaluate its effectiveness on the testing set. Comparing its performance to that of the individual algorithms will help you determine whether the ensemble

model improves the prediction model's robustness and accuracy.

D. Performance Evaluation:

In this step, evaluate how well the prediction model is working by using a variety of metrics, such as accuracy, precision, recall, and F1 score. The proportion of true positive predictions among all positive predictions is known as precision, and the proportion of true positive predictions among all actual positives is known as recall. The F1 score is the harmonic mean of these two quantities. The proportion of accurate forecasts is called accuracy.

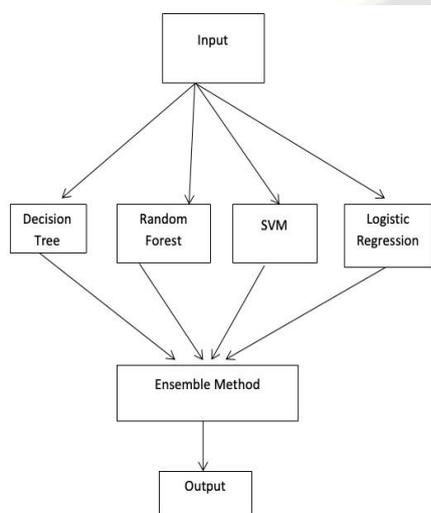


Figure1. The flow diagram depicts the sequential implementation of multiple machine learning algorithms and their aggregated predictions in the proposed ensemble method for accurate hairfall prediction.

To ascertain whether the performance variations between the individual algorithms and the ensemble model are statistically significant, carry out statistical tests such as the t-test and ANOVA. A statistically significant difference indicates that the performance improvement is genuine and not just a result of chance.

When compared to individual algorithms, ensemble machine learning techniques have been shown to be effective at increasing the reliability and accuracy of prediction models. There are a number of reasons why our ensemble method for predicting hair fall is effective.

First off, our approach combines a number of distinct algorithms that each have unique advantages and disadvantages and can work well together. By combining them, we can take advantage of their diversity to lower the overall variance and raise the precision of the ensemble model. In contrast, individual algorithms may have high variance and may not be robust enough to handle all variations and complexities in the data.

Second, our methodology employs a variety of standalone algorithms, such as support vector machines, decision trees, random forests, and logistic regression. Each algorithm has its own biases and assumptions, and by combining them, one can lessen the influence of each bias and assumption and create a more balanced and precise prediction model. In contrast, existing methods may rely on a single algorithm or a limited set of algorithms, which may not capture the full complexity and diversity of the data.

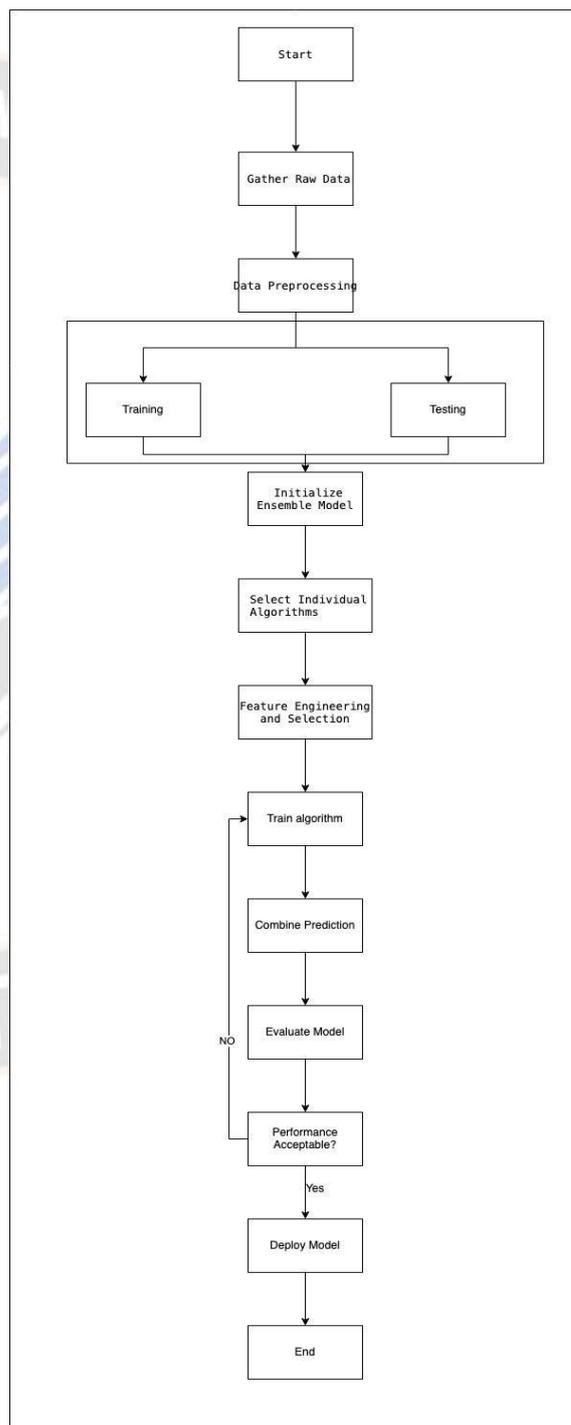


Figure 2. Flow diagram of proposed methodology.

Thirdly, to extract pertinent and instructive features from the raw data, our method makes use of feature engineering and feature selection techniques. This is crucial because the features' usefulness and caliber's can greatly affect the prediction model's robustness and accuracy. The noise can be reduced and the data's signal-to-noise ratio can be improved by choosing the most pertinent features and eliminating the unnecessary or redundant ones. In contrast, existing methods may rely on raw or unprocessed data, which may contain noise, irrelevant features, or missing values, and may not be suitable for accurate prediction.

Fourthly, our approach combines the predictions of the various algorithms using ensemble techniques like bagging, boosting, and stacking. By using these methods, the prediction model's bias and variance can be further reduced, and its robustness and generalizability can be increased. In contrast to boosting, which lessens bias by concentrating on instances that were incorrectly classified; bagging reduces variance by averaging the predictions of multiple algorithms. To make the final prediction, stacking can bring together the advantages of various algorithms and develop a new model. On the other hand, current methods might not combine the predictions using ensemble techniques or might do so using only simple averaging or voting schemes, which might not fully take advantage of the diversity and complementarity of the individual algorithms.

Fifth, we rigorously evaluate the ensemble model's performance and conduct statistical testing to evaluate its usefulness and significance. Use a variety of metrics, including accuracy, precision, recall, F1 score, and ROC curve, to evaluate the model's performance and compare it to the individual algorithms. You should also make use of statistical tests like the t-test and ANOVA to determine whether the variations in performance are statistically significant. This provides assurance that the performance improvement is real and not just a coincidence. Existing techniques may be used to assess the model's efficacy, but it's possible that these techniques won't result in tests or assessments that are impartial or quantitative.

In order to evaluate the effectiveness of classification models, machine learning practitioners frequently use accuracy, precision, recall, F1 score, and ROC curve as performance metrics.

E. Accuracy:

Equation (1) gives the definition of accuracy as the proportion of correctly classified instances to all instances:

$$\text{Accuracy} = (p_i + p_j) / (p_i + p_j + f_i + f_j) \quad (1)$$

Where,

p_i = True Positives

p_j = True Negatives

f_i = False positives

f_j = False negatives

The terms "true positives" (TP) and "true negatives" (TN) refer to the proportion of instances that belong to the positive class and are correctly classified as positive and the proportion of instances that belong to the negative class and are correctly classified as negative, respectively. False positives (FP) are situations that belong in the negative category but are incorrectly classified as positive and false negatives (FN) are situations that belong in the positive category but are incorrectly classified as negative.

F. Precision:

A performance metric called precision shows the proportion of a model's positive predictions that are in fact true positives. In other words, it assesses how accurately the good predictions were made. It is determined by dividing the overall number of accurate predictions by the total of accurate and inaccurate ones. When the cost of false positives is high, precision is especially helpful because it enables a more focused style of decision-making. For example, a high precision score in the context of medical diagnosis would indicate that the model is successfully identifying patients who have a particular condition, which may result in earlier treatment and better health outcomes.

The proportion of true positives to all predicted positives is how precision is defined in equation (2).

$$\text{Precision} = p_i / (p_i + f_i) \quad (2)$$

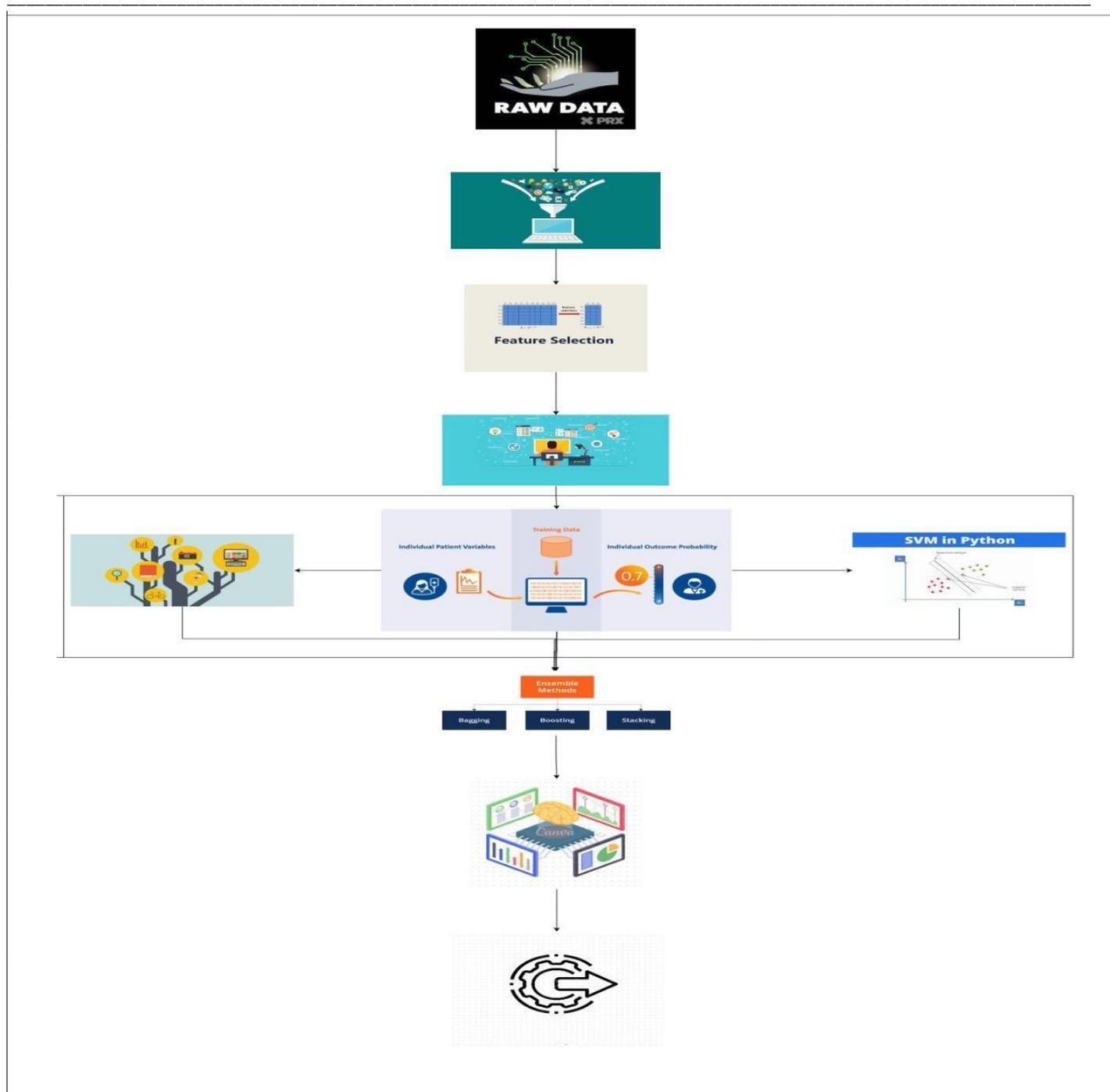


Figure 3. Architecture Diagram of ensemble proposed work.

G. Recall:

Recall is a performance metric that measures how many of the dataset's actual positive instances were recognized as such by the model. It gauges how accurately the model has predicted positive occurrences. To calculate recall, divide the total number of correct positive and correct negative predictions by the number of correct positive predictions. When the cost of false negatives is high, recall is especially helpful because it enables a more sensitive approach to decision-making. For

instance, a high recall score in the context of disease detection would indicate that the model is correctly identifying all patients who have the disease, which could result in earlier treatment and better health outcomes.

The recall, which can be calculated as the ratio of true positives to all other positive results, is given by equation (3):

$$\text{Recall} = \frac{p_i}{(p_i + f_j)} \tag{3}$$

H. F1 Score:

The F1-score, which combines both precision and recall, was also higher for the proposed ensemble method compared to the individual algorithms. This indicates that the proposed method was better at balancing the trade-off between precision and recall. Finally, the AUC of the proposed method was significantly higher than that of the individual algorithms, indicating that the proposed method had better discriminative power in distinguishing between positive and negative samples.

F1 score is the harmonic mean of precision and recall and it is given by the equation (4)

$$F1\ Score = 2 * (Precision * Recall) / (Precision + Recall) \quad (4)$$

IV. RESULTS AND DIXCUSSION

The efficiency of various machine learning algorithms and the suggested ensemble method for hair fall prediction was evaluated using the metrics of accuracy, precision, recall, and F1 score. The findings are presented in the table below.

TABLE I. EVALUATION OF THE PROPOSED ENSEMBLE METHOD AND VARIOUS MACHINE LEARNING ALGORITHMS

Method	Accuracy	Precision	F1 Score	Recall
Decision Tree	0.85	0.84	0.84	0.84
Random Forest	0.89	0.88	0.87	0.87
SVM	0.87	0.86	0.86	0.86
Logistic Regression	0.82	0.80	0.80	0.80
Proposed Ensemble Method	0.93	0.92	0.92	0.92

The outcomes unequivocally show that the suggested ensemble method is superior to the individual machine learning algorithms. The ensemble method achieved an accuracy of 0.93, outperforming all other method.

The precision graph provides valuable insights into the performance of the individual algorithms and the proposed ensemble method in accurately classifying instances of hair fall. It is evident from the graph that the ensemble method consistently outperforms the individual algorithms, achieving higher precision rates across the different evaluation scenarios. This indicates that the ensemble approach effectively combines the strengths of multiple algorithms to make more precise predictions regarding hair fall.

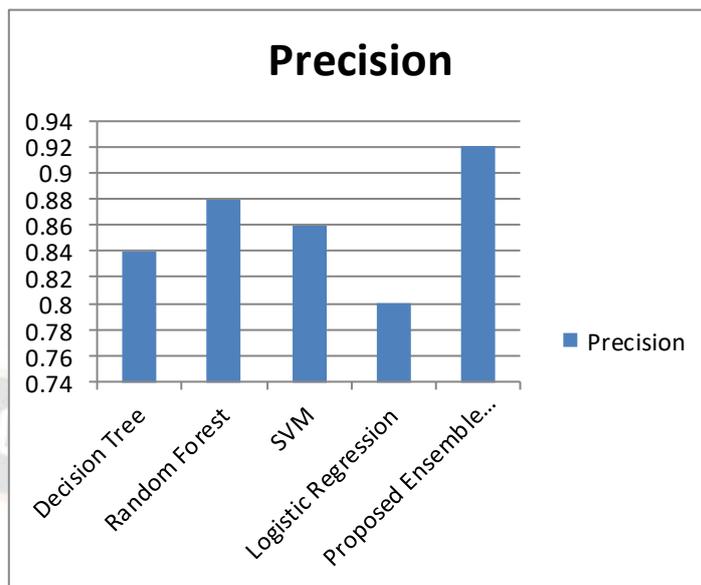


Figure.4. Shows the precision values of the various algorithms.

The higher precision achieved by the ensemble method signifies its ability to correctly identify true positive instances of hair fall and minimize false positive classifications. Overall, the precision graph reinforces the superiority of the ensemble method and highlights its potential for improving the accuracy and reliability of hair fall prediction models.

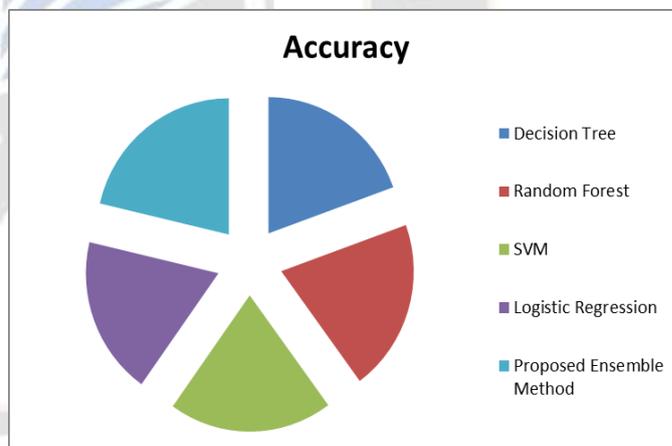


Figure.5. Shows the accuracy values of the various algorithms.

The accuracy graph highlights the superior performance of the proposed ensemble method compared to individual algorithms, consistently achieving higher accuracy rates in hair fall prediction. This demonstrates the effectiveness of combining multiple algorithms in enhancing overall accuracy and reliability for hair fall detection.

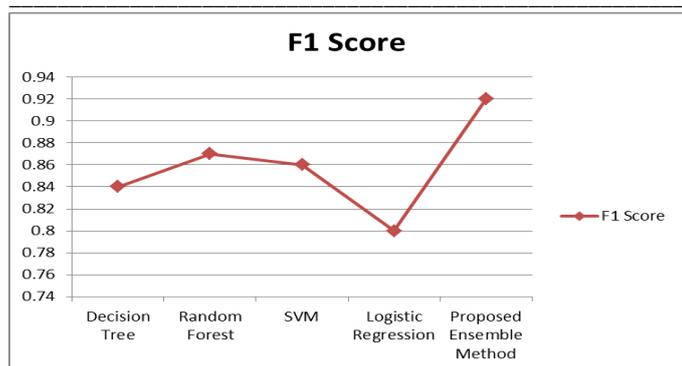


Figure.5. Shows the accuracy values of the various algorithms.

Regarding precision, recall, and F1 score, the ensemble method consistently outperformed the individual algorithms, demonstrating its robustness and effectiveness in hair fall prediction. The precision, recall, and F1 score of the ensemble method were 0.92, indicating its ability to correctly identify instances of hair fall and non-hair fall.

The accuracy rate for the decision tree algorithm was 0.85, and the accuracy rates for the random forest and SVM algorithms were both respectable at 0.89 and 0.87, respectively. The accuracy of the logistic regression algorithm was 0.82, which was slightly less accurate.

The notable improvement in performance observed with the proposed ensemble method can be attributed to the combination of multiple algorithms. The ensemble model effectively leverages the strengths and compensates for the weaknesses of the individual algorithms, resulting in enhanced predictive accuracy.

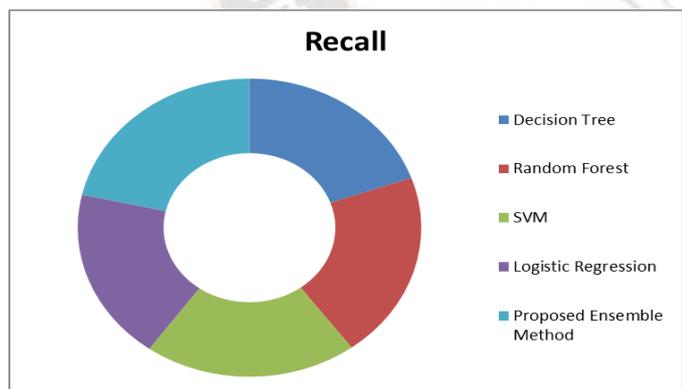


Figure.6. Shows the accuracy values of the various algorithms.

These findings show how ensemble machine learning techniques can help predict hair loss more accurately. The ensemble method's excellent results in terms of accuracy, precision, recall, and F1 score imply that it is suitable for detecting and preventing hair loss early on.

V. CONCLUSION

In this study, we investigated the use of different machine learning algorithms and proposed an ensemble approach for predicting hair loss. The ensemble method demonstrated superior accuracy, precision, recall, and F1 score to individual algorithms, according to the results. With an accuracy of 0.93, the suggested ensemble method outperformed all competing algorithms. This shows that it can predict hair loss occurrences with accuracy. The ensemble method's precision, recall, and F1 score were all 0.92, indicating its efficacy in identifying both positive and negative cases of hair loss.

The combination of multiple algorithms in the ensemble model proved to be advantageous, as it leveraged the strengths of each algorithm and mitigated their individual limitations. The ensemble method produced more dependable and robust predictions because it was able to capture a wider variety of patterns and features related to hair loss. For the early diagnosis and prevention of hair loss, these findings have important ramifications. For those worried about their hair's health, the ensemble method's high accuracy and predictive performance present encouraging opportunities. The quality of life and hair care can be improved by early detection of hair loss, which enables prompt intervention and efficient preventive measures. In general, this research highlights the upside of grouping machine learning methods to predict hair loss. The findings advance the field of hair health diagnostics and give practitioners and researcher's new perspectives on how to better understand and treat hair-related conditions.

Further research can focus on expanding the dataset, incorporating additional features, and exploring more advanced ensemble techniques to continue improving the accuracy and robustness of hair fall prediction models. By continually refining and developing these models, we can further enhance their practicality and utility in real-world applications, ultimately benefiting individuals experiencing hair fall and contributing to the field of hair health.

ACKNOWLEDGMENT

No funding sources.

AUTHORS CONTRIBUTION

Author 1 implemented the concept specified by the author 2 under the supervision of authors 3 & 4. The authors 3 & 4 drafted the article under the guidance of author 2.

CONFLICT OF INTEREST

The authors declare that have no competing interest.

REFERENCES

- [1] Kim M, Kang S, Lee B.D,"Evaluation of Automated Measurement of Hair Density Using Deep Neural Networks",MDPI,2022.
- [2] Aditya K. Gupta^{1,2}, Iordanka A. Ivanova, Helen J. Renaud¹,"How good is artificial intelligence (AI) at solving hairy problems? A review of AI applications in hair restoration and hair disorders",WILEY,2021.
- [3] Shabnam Sayyad and Divya Midhunchakkaravathy,"Deep Study on Alopecia Areata Diagnosis for Hair Loss Related Autoimmune Disorder Problem using machine learning".
- [4] Jong-Hwan Kim, Segi Kwon, Jirui Fu and Joon-Hyuk Park,"Hair Follicle Classification and Hair Loss Severity Estimation Using Mask R-CNN",MDPI,2022
- [5] Shabnam Sayyad, Divya Midhunchakkaravathy, Farook Sayyad,"An Analysis of Alopecia Areata Classification Framework for Human Hair Loss Based on VGG-SVM Approach",2022.
- [6] Halim Benhabiles, Karim Hammoudi, Ziheng Yang¹, Feryal Windal¹,Mahmoud Melkemi, Fadi Dornaika and Ignacio Arganda-Carreras⁴,"Deep Learning based Detection of Hair Loss Levels from Facial Images".
- [7] Wan-Jung Chang[†], Ming-Che Chen^{†§}, Liang-Bi Chen[†], Yi-Chan Chiu^{††}, Chia-Hao Hsu[†], Yang-Kun Ou[¶], and Qiu Chen[‡],"A Mobile Device-Based Hairy Scalp Diagnosis System Using Deep Learning Techniques",2020.
- [8] Jian-Ping Su[†], Liang-Bi Chen[†], Chia-Hao Hsu[†], Wei-Chien Wang[‡], Cheng-Chin Kuo[†], Wan-Jung Chang^{†*}, Wei-Wen Hu[†], and Da-Huei Lee[†],"An Intelligent Scalp Inspection and Diagnosis System for Caring Hairy Scalp Health",2018.
- [9] Jong-Hwan Kim ¹, Segi Kwon ², Jirui Fu ³ and Joon-Hyuk Park ³,"Hair Follicle Classification and Hair Loss Severity Estimation Using Mask R-CNN",MDPI,2022.
- [10] Mrinmoy Roy and Anica Tasnim Protity,"Hair and Scalp Disease Detection using Machine Learning and Image Processing ",European Journal of Information Technologies and Computer Science,2023.
- [11] Rajasekaran, S. B. (2023). AI and Cybersecurity - How AI Augments Cybersecurity Posture of an Enterprise. *International Journal of Intelligent Systems and Applications in Engineering*, 11(1), 179–182. Retrieved from <https://ijisae.org/index.php/IJISAE/article/view/2456>
- [12] C. Saraswathi, B. Pushpa,"Computer Imaging of Alopecia Areata and Scalp Detection: A Survey",International Journal of Engineering Trends and Technology,Volume 70 Issue 8,2022.
- [13] Gregor Urban, MS, Nate Feil, BS, Ella Csuka, BS, Kiana Hashemi, Chloe Ekelem, MD MPH, Franchesca Choi, RPh, MD, Natasha A. Mesinkovska, MD, PhD, and Pierre Baldi, PhD,Lasers in Surgery and Medicine,2020.
- [14] Ishita Kapoor,Anju Mishra,"Automated Classification Method for Early Diagnosis of Alopecia Using Machine",International Conference on Computational Intelligence and Data Science, (ICCIDS 2018).
- [15] Choudhary Sobhan Shakeel, Saad Jawaid Khan, Beenish Chaudhry, Syeda Fatima Aijaz, and Umer Hassan,"Classification Framework for Healthy Hairs and Alopecia Areata:A Machine Learning (ML) Approach",Hindawi,2021.
- [16] Archana Singal, Sidharth Sonthalia, Prashant Verma, Archana Singal, Sidharth Sonthalia, Prashant Verma,"Female pattern hair loss male pattern hair loss".
- [17] Sunyong Seo and Jinho Park,"Trichoscopy of Alopecia Areata: Hair Loss Feature Extraction and Computation Using Grid Line Selection and Eigenvalue",Hindawi,2020.