



Evaluation Report

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Executive Summary

This report evaluates the results of our predictive modeling project for male pattern baldness classification by using both tabular and image-based datasets. The report reflects on the clarity and usefulness of our results, highlights key findings such as the improvement gained from segmentation and CLAHE filtering, and ranks models based on their real-world applicability. It also assesses whether the models meet the original goals set at the beginning of the project, from both a technical and practical perspective, identifies questions raised by our analysis, and suggests possible directions for future work. Furthermore, it includes a review of the models selected for final use. The first appendix provides supporting charts, classification reports, and visual summaries that reinforce the evaluation, including insights from merged survey data, top model comparisons, and per-class performance breakdowns, for both tabular and image based models. The report concludes with an additional appendix that outlines all the 5 datasets used in the project, including their sources and a brief description of each one.



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1. Evaluating the Results

After testing and comparing our models on both the tabular (Mendeley) and image-based (Roboflow) datasets, we assessed how well the results align with the original project goals, while improving the accuracy and practical usability of male pattern baldness stage prediction using machine learning and deep learning.

Are your results stated clearly and in a form that can be easily presented?

The results are clearly presented in visual charts and confusion matrices in the Modeling Report. Key findings such as model accuracy, F1 scores, and class-specific insights were broken down for each algorithm. This structure makes it easy to communicate model performance both to technical and non-technical stakeholders.

- Best tabular model: XGBoost (accuracy = 0.8144)
- **Best image-based model**: ResNet18 (F1 = 0.7668, test accuracy = 0.8558)
- **Best preprocessing improvement**: Segmentation + CLAHE, which increased both accuracy and F1 score by ~15%

Are there particularly novel or unique findings that should be highlighted?

- Applying segmentation to isolate the hair region, followed by CLAHE for image contrast, significantly improved classification quality, especially for stages with subtle scalp differences.
- Even lightweight models like EfficientNet-B0 and MobileNetV3-Large showed strong performance with proper preprocessing.
- Across nearly all CNN models, Level 5 Norwood classification was a consistent challenge, which suggests a need to either merge this level with Level 4 or 6, or explore targeted oversampling or augmentation strategies.



Model Ranking by Applicability

The models were ranked in the Modeling Report by a mix of accuracy and practical value. It is safe to say that these models can be recommended for further development or deployment depending on whether structured data or visual scalp data is available in a given clinical context.

Tabular Models (Hair Fall Causes Dataset)

Model Name	Accuracy
XGBoost	0.8144
K-Nearest Neighbors (KNN)	0.8041
Random Forest (GridSearchCV)	0.8041

Image Models (Scalp Image Dataset)

Model Name	Accuracy	F1 Score
ResNet18	0.86	0.7668
MobileNetV3-Large	0.86	0.75
EfficientNet-B0	0.85	0.75
ConvNeXt-Tiny	0.85	0.75

How Well The Results Answer Business Goals

The core business goal was to build a working prototype that could predict hair loss stages and/or risk levels in men. Based on our results:

- Tabular model (XGBoost) is effective for quick assessments using survey or clinical data.
 Additionally, it offers the ability to customize and suggest personalized treatment plans or preventative measures for hair loss.
- **Image models** show clear potential for a diagnostic app, as they can classify scalp images with reasonably high accuracy.



• These findings collectively can facilitate early-stage screening and promote more tailored treatment plans or preventative approaches.

Follow-up Questions Raised

- How can we improve predictions for Level 5 without increasing data volume? (e.g., smarter augmentation, merging stages)
- Is it possible to combine the predictions from tabular and image models to improve final decision-making?
- Would larger image datasets with more balanced stage representation lead to better classification of stages like Norwood 5–7?
- Can additional personal attributes (e.g., hormones, diet) improve tabular model performance (e.g. improve correlation between features)?

Our Approved Models

Below is the list of approved models for the final report. These models align with both data science standards and business goals:

- **XGBoost**: Best tabular model in terms of accuracy and generalization. Recommended for numerical clinical intake forms.
- **ResNet18**: Strong overall image classifier with high F1 score and good handling of moderate and advanced stages.
- EfficientNet-B0 (another option for an image deep learning model): Balanced accuracy with the benefit of being resource-efficient and fast.



2. Review Process

Looking back at our project, there were several things that worked well and a few areas we would approach differently in the future.

- One of the biggest successes was the decision to treat this as a multi-modal task. Using both tabular and image datasets gave us a broader perspective and let us explore different modeling techniques. This also made our final results stronger, since we could evaluate hair fall risk in two different ways: survey data and scalp images. Scalp images can be exclusively used for classifying male pattern baldness. Survey data can then be leveraged to recommend preventative measures, tailored to the predicted stage of baldness.
- Another key choice that paid off was applying segmentation and CLAHE preprocessing to the scalp images. At first, the models gave lower accuracy (around ~64%), but after improving the image quality and removing background noise, our top models reached ~86% test accuracy. That showed us the value of investing time in the preprocessing phase, especially for medical imaging.
- In terms of what could be improved, we spent a lot of time tuning deep learning models manually. Looking back, we could have automated the training pipeline a bit more to compare models faster. Also, **Level 5** Norwood was a consistent weak spot across models, and earlier exploration of class merging or smarter augmentation could have helped.
- Lastly, coordinating the merging of datasets and keeping labels aligned (especially between Norwood levels) took a while. For next time, we would document data transformations more thoroughly to save time.
- The experience helped us understand the strengths and limits of combining structured data
 with image classification. We gained hands-on practice with real-world data issues and are
 now more confident in applying machine learning to health-related use cases. Furthermore,
 earlier integration of business stakeholders might help align technical outcomes with practical
 expectations sooner.

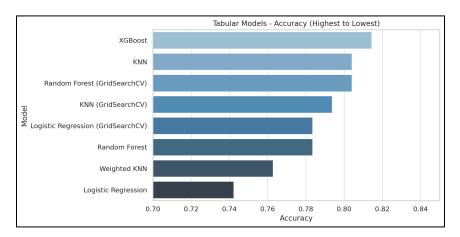


Appendix: Key Graphs and Performance Tables

Hair Fall Causes Dataset (Mendeley) + Merged Google Forms Responses

Comparison Between Top 8 Tabular Models

Model	Accuracy	Notes	
XGBoost	0.8144	Best performance overall	
KNN	0.8041	Very good, minimal tuning	
Random Forest (GridSearchCV)	0.8041	Good balance & interpretability	
KNN (GridSearchCV)	0.7938	Slight improvement over KNN	
Logistic Regression (GridSearchCV)	0.7835	High recall for 'Yes'	
Random Forest	0.7835	Good but not optimized	
Weighted KNN	0.7629	More balanced but lower	
Logistic Regression	0.7423	Baseline model	

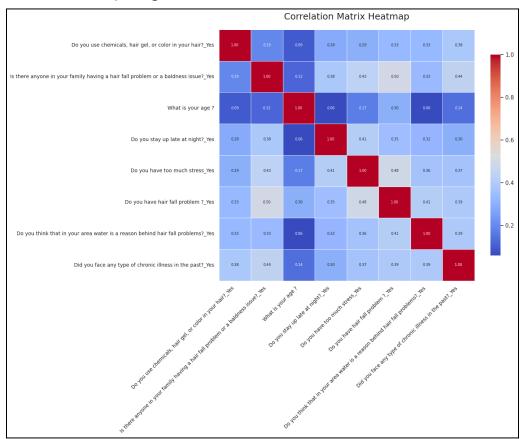


Bar chart comparing the accuracy of the top 8 tabular models - XGBoost achieved the highest accuracy (0.8144), followed closely by KNN and Random Forest with GridSearchCV. Logistic Regression (default) performed the weakest, serving as a baseline reference.



Features Correlation Matrix (After Merging Google Form Responses)

• The following charts and graphs present the values included in the final dataset after merging the records from the Google Forms responses. **Interestingly, after adding the new records, we observed a surprising decrease in the correlation values between the features.**

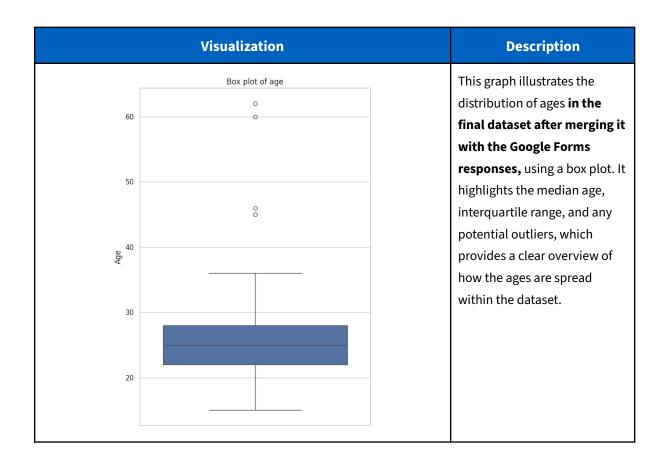


Feature	Correlation with Target
Do you have hair fall problem ?	1
Is there anyone in your family having a hair fall problem or a baldness issue?	0.497499
Do you have too much stress?	0.483251
Do you think that in your area water is a reason	0.408046

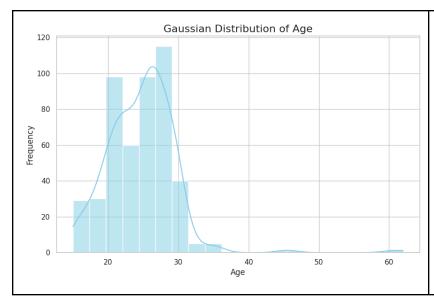


behind hair fall problems?	
Did you face any type of chronic illness in the past?	0.390889
Do you use chemicals, hair gel, or color in your hair?	0.351738
Do you stay up late at night?	0.330020
What is your age?	0.296860

Additional Visualizations

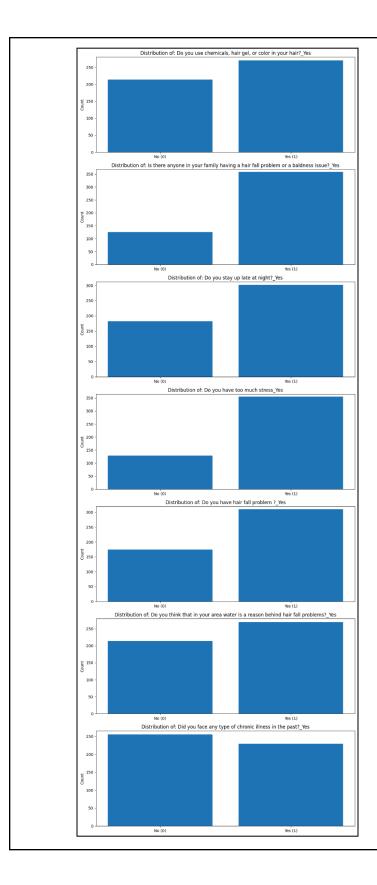






This graph illustrates the distribution of participants' ages, following a bell-shaped Gaussian curve, with most responses concentrated around the 20s to early 30s.





This graph shows how many participants answered "Yes" or "No" for each question in the dataset, which helps seeing the distribution, as well as which factors were more common across the responses



Classification Report For XGBoost (Accuracy: 0.8144)

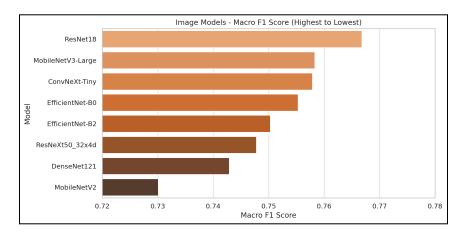
Class	Precision	Recall	F1-Score	Support
0 (No Hair Fall)	0.71	0.67	0.69	30
1 (Hair Fall)	0.86	0.88	0.87	67
Accuracy	-	-	0.81	97
Macro Average	0.78	0.77	0.78	97
Weighted Average	0.81	0.81	0.81	97



Scalp Image Combined Datasets (Roboflow)

Comparison Between Top 8 Images Models

Model	Test Accuracy	Macro F1	Notes
ResNet18	0.86	0.7668	Top performer, lightweight
MobileNetV3-Large	0.8582	0.7583	High balance and accuracy
EfficientNet-B0	0.8606	0.7553	Efficient and strong
ConvNeXt-Tiny	0.8534	0.7579	Strong on rare classes
DenseNet121	0.8413	0.7429	Balanced across stages
ResNeXt50_32x4d	0.863	0.7478	High accuracy, lower F1
MobileNetV2	0.8293	0.7301	Lightweight, good generalization
EfficientNet-B2	0.8438	0.7503	Slightly lower accuracy



Bar chart comparing the macro F1 scores of the top 8 image models - ResNet18 achieved the highest F1 score (0.7668), indicating strong overall performance across Norwood stages. MobileNetV3-Large, ConvNeXt-Tiny, and EfficientNet-B0 followed closely, while MobileNetV2 showed the lowest F1 score among the top models.



Image Count per Norwood Level (Train/Valid/Test) After Combining Two Roboflow Datasets and Applying Segmentation + CLAHE

This table summarizes the number of images per Norwood level (2–7) in the **train**, **validation**, and **test** folders in our two combined Roboflow image datasets.

Level	Train	Valid	Test	Total
Level 2	3963	388	210	4561
Level 3	2139	210	95	2444
Level 4	1149	125	51	1325
Level 5	712	77	13	802
Level 6	572	42	20	634
Level 7	534	53	27	614
Total	9069	895	416	10380

Improvement from Preprocessing Table (CLAHE + Segmentation)

Stage	Test Accuracy	Macro F1
Before Segmentation	~0.64	~0.60
After Segmentation + CLAHE	0.86	0.76

Classification Report For ResNet18 Per-Class F1 Scores (Overall F1-Score 0.7668)

Norwood Level	F1-Score
Level 2	0.932
Level 3	0.8308
Level 4	0.7475
Level 5	0.3429
Level 6	0.8696
Level 7	0.9057



Appendix: Data Sources

For this project, we utilize **5 datasets** from different sources:

• Tabular Model

- Hair Fall Causes Dataset (Mendeley)
 - i. Source: Mendeley data repository
 - ii. Description: This dataset consists of 717 survey responses from male and female participants regarding hair care habits, health conditions, and lifestyle choices that may influence hair loss. The data was collected via Google Forms distributed across social media and online communities. The survey is available for downloading either as a CSV or XML file. The survey dataset is the sole content of the respiratory.

Google Forms Survey Responses

- i. Source: חיזוי נשירת שיער
- ii. Description: We created a Google Form mirroring the original dataset's features and structure to enrich it. The 24 additional male survey responses were cleaned, formatted, and merged using Python. After preprocessing, removing irrelevant columns, and excluding female entries we identified strongly correlated features with the target variable. The remaining data resulted in 483 male responses (7 features and 1 target variable).

Images Model

- Scalp image dataset (Roboflow) 1
 - i. **Source:** Roboflow dataset repository
 - ii. **Description:** This dataset includes a total of **2,317 images** of male scalps photographed from multiple angles, including front, back, left, right, and top-down views. The images are labeled according to Norwood stages 2–7 that represent various degrees of male pattern baldness. The dataset is split into training (87%), validation (9%), and test (4%) sets, resulting in 2,009 training images, 209 validation images, and 99 test images. To align the labels to our original dataset, we merged **Level 1 and Level 2** in the new dataset and then integrated it with our own.



Scalp image dataset (Roboflow) 2

i. Source: Roboflow dataset repository

ii. Description: This dataset contains a total of **8,084 scalp images** captured from a top-down angle, each labeled with a Norwood stage 1-7. The dataset is pre-split into train (87%), validation (8%), and test (4%) sets, resulting in 7,060 training images, 686 validation images, and 338 test images.

PyTorch Hair Segmentation GitHub Repository

i. Source: YBIGTA/pytorch-hair-segmentation GitHub repository

ii. **Description:** This dataset obtained from GitHub contains annotated images for hair segmentation tasks. Each image is paired with a corresponding segmentation mask that outlines the hair region, enabling us to train a model that detects and isolates the scalp area. We used this dataset to build a segmentation pipeline that improved classification performance by focusing the model on relevant scalp regions.

