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LEVERAGING MACHINE LEARNING METHODS IN PREDICTING AND ANALYZING THE ASSOCIATION BETWEEN DIETARY INFLAMMATORY INDEX AND ALOPECIA

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ABSTRACT

Alopecia areata (AA) is considered a chronic inflammatory disorder and represents a worldwide public health problem. Diet was hypothesized to play a role in AA development, but little is known about the association between the dietary inflammatory index (DII) and AA. This study aimed to analyze the correlation between AA and DII using machine learning at aj(ML) models. DII scores were ascertained using a food frequency questionnaire (FFQ), and the Severity of Alopecia Tool (SALT) score was used to classify the severity of AA. Three machine learning models were developed: K-Nearest Neighbors (KNN) with dimensionality reduction to prevent overfitting, Logistic Regression with L2 regularization, and Random Forest enhanced through grid search for hyperparameter tuning. Additionally, to further understand the association between DII and AA, partial dependence plots (PDPs), correlation analysis, and multiple evaluation indicators, including accuracy, F1 score, recall, precision, and area under the receiver operating characteristic curve (ROC AUC) were used. Surprisingly, higher DII scores are significantly associated with an increase in AA. In addition, a higher inflammatory diet was associated with increased severity of the disease. The highest accuracy was achieved by the Random Forest Classifier 98.77%, whereas 98.64% and 98.10% were achieved by Logistic Regression and KNN models, respectively. This study presents evidence about the association between inflammatory food patterns and AA, which may provide important implications for future treatment and dietary interventions. A high score on the DII indicated an increased proinflammatory potential of food intake and was associated with an increase in AA.

KEYWORDS*:* Machine Learning, Dietary inflammatory index, alopecia areata, osteopenia, SALT score, Hair loss.

1. INTRODUCTION:

Alopecia areata (AA), an autoimmune disorder, results in non-scarring, patchy hair loss on the face, scalp, and occasionally other body areas (Gilhar *et al*., 2019). Alopecia areata commonly manifests before age 30, affecting both males and females equally (Madani & Shapiro, 2000). Because of its effect on appearance, AA induces psychological stress (Saif *et al*., 2019). Therefore, it is important to develop approaches for AA prevention to reduce psychological stress and suffering in individuals. An unhealthy diet is the main risk factor**.** Although, a strong correlation is yet to be confirmed by other studies, it is well established that Comorbidities related to AA include low-grade inflammation (Norde *et al*., 2019). Furthermore, earlier research has indicated that diet has been shown to influence the levels of inflammatory mediators and the formation of AA, thus, the Dietary Inflammatory Index (DII) becomes a relevant tool.

The DII is an index that was recently developed to assess the overall pro-inflammatory potential of dietary components based on their associations with inflammation. It is designed to assess average daily intake across countries (Shivappa *et al*., 2014). For example, (Darbandi *et al*., 2021) showed that an intervention based on DII can be effective in improving chronic systemic inflammation, obesity, diabetes, cancer, cardiovascular disease, and fatty liver disease. While nutrients and foods, such as vitamins E and C, vegetables, fruits, and whole grains, have been shown to have anti-inflammatory effects (Upritchard *et al*., 2000; Chrysohoou *et al*., 2004), it is important to note that these effects can vary based on individual factors like genetics, gut microbiota, and lifestyle (Bagh
eri et atal., 2022). On the other hand, studies showed that short-chain carbohydrates, simple sugars, refined cereals, red meat, and high-fat dairy are related to inflammatory markers (Esmaillzadeh *et al*., 2007). However, recent research has suggested this connection might not be so simple. A recent example is a study published in The American Journal of Clinical Nutrition, in which red meat consumption was not directly positively associated with inflammatory markers when adjusted for body mass index (BMI), which the authors suggested might be a larger determinant of inflammation (Wood et al., 2023). That covers a spectrum of possibilities in research results and that individual behaviors matter for diet. The DII assesses multiple dietary components including food groups, nutrients, and inflammatory potential. This is valuable, as the diet composition is addressed rather than focusing on selected one or two minerals or foods (Wood *et al.*, 2015; Moludi *et al.*, 2022). In addition, the rating system is derived from the results of peer-reviewed papers rather than population means or recommended dietary intakes (Wood et al., 2015). Finally, where follicular-centric inflammation is responsible for hair loss the eventual replacement of follicles with fibrous tissue may occur (Somani *et al*., 2008). AA has previously been implicated for its association with inflammation (Mirmirani *et al*., 2005).

Machine learning (ML), a sub-branch of artificial intelligence (AI), has become a very promising and powerful tool in all sciences thanks to its data-driven character providing insights and predictions. It has shown great potential applications in healthcare, for instance, in disease diagnosis ((Mohammed & Tayfor, 2024)), autism classification (Hassan & Taher, 2022), personalized treatment (Kohli e., 2022) and COVID-19 prediction (Hassan & Ahmed, 2023). Similarly, photos of affected skin areas can be a, nalyzed by machine learning to identify patterns, helping dermatologists and physicians detect skin diseases and, when applicable, begin treatment sooner (Ahammed *et al*., 2022).

But, the use of machine learning in healthcare poses important challenges (Paleyes *et*., 2022). First, it can be both arduous and time-consuming to collect high-quality and diverse data types. Second, data cleaning and engineering operations are highly critical to getting accurate and intended results, and they involve careful handling of missing values, outliers, and *noise.*

Also, feature engineering, which is the task of selecting and transforming the features that are input to the model, necessitates domain knowledge and a massive effort to extract valuable insights from the raw data. A recent study on machine learning addressed in health care showed that machine learning highly implementable algorithms in the field of skin conditions by testing the diagnostic accuracy of the models in diagnosing skin disorders such as AA through dermoscopy images (Anand *et al*., 2022). Similarly, (Saraswathi *et al* . Saraswathi & Pushpa, 2023), highlighted the potential of a machine learning algorithm designed for classifying Alopecia Areata usingat human scalp hair images.

Despite these advancements, challenges persist in implementing machine learning models effectively. The scarcity of annotated datasets for dermatological conditions like AA impedes the development and validation of robust models. Furthermore, the interpretability of machine learning models in healthcare remains a concern, as clinicians often need clear explanations of model predictions to trust and adopt these systems in practice.

However, there is no evidence linking the DII score to the risk of developing AA. We propose leveraging machine learning methods in exploring the relationship between DII and Alopecia.

2. METHOD:

Study design and participants

This single-center cross-sectional study was conducted from October 2023 to December 2023 to assess dietary, lifestyle, and health-related factors among Kurdish adults (mean age: 53.84 ± 7.75 years) who were sent to dermatology clinics in Kalar City, located in the Kurdistan region of Iraq. Initially, a total of 440 participants were selected for the survey based on prior research conducted in Kalar City. Participants were recruited through voluntary participation, where individuals responded to open invitations distributed via local community centers and social media platforms; 440 participants were selected for the survey based on prior research conducted in Kalar City (Fateh *et al*., 2022). Recruitment criteria ensured a diverse representation of individuals within the target demographic. During face-to-face interviews, a professionally trained interviewer administered a detailed questionnaire. This included sections on:

- **Demographics:** Age, sex, marital status, highest degree.
- **Socioeconomic status:** Income, employment status, and household characteristics.
- **Physical activity:** How often and intensely and what kinds of activities you do.
- **Medical history:** Chronic or acute conditions, medications, and family health history.
- **Dietary intake:** Participants' food consumption and caloric intake through a validated Food Frequency

Questionnaire (FFQ) were used to measure dietary intake.

This study was approved by the Ethics Committee of Garmian Polytechnic University, Kalar Technical Institute. All methods were implemented according to guidelines and regulations. Oral and written informed consent were provided to all the participants. This research was carried out by the Declaration of Helsinki. Accordingly, informed written consent was obtained from all participants prior to data collection. To preserve the validity of the analysis, strict a priori exclusion criteria were implemented, and as a result, participants were excluded from the study if they reported a caloric intake of less than 800 kcal or greater than 4200 kcal/day. These cut-offs were used to remove implausible dietary reports that probably arise from underreporting or overreporting. Intakes less than 800 kcal/day are too low to cover basic metabolic functions, with such low levels likely stemming from either incomplete dietary assessment or underreporting, while intakes greater than 4200 kcal/day were established as physiologically unfeasible for population sample distributions, suggesting potential overreporting or data entry errors. This range is commonly applied in nutritional epidemiology studies to enhance data quality and validity and thus ballpark over- or under-reporting or published incomplete data regarding dietary exposure or may have had a pathological condition that may have interfered with the results of the trial, such as cancer, cardiovascular diseases, thyroid diseases, or any inflammatory disease. We then applied these exclusion criteria, leading to the final 427 individuals included for the study. Such a broad selection process gives a good grounding to explore the relationship between diet, lifestyle factors and health outcomes. These findings can be combined to implement informed healthcare plans and nutritional information for the Kurdish population.

Physical activity

Physical activity was assessed using the short-form version of the International Physical Activity Questionnaire (IPAQ-SF), a reliable tool. low levels of physical activity were defined based on the weekly amount of METs on a scale of MET-min/week: very low (<600), low (600-3000), and moderate/high (>3000) (Wareham *et al*., 2003).

Anthropometry

Each individual was weighted using the InBody 770 scale (Inbody Co, Republic of Korea) while wearing minimal clothing and no shoes. The scale has a 100-gram accuracy. Without shoes, height was measured with a BSM 370 automated stadiometer from Biospace Co. Republic of Korea, which has an accuracy of 0.1 cm.

Blood tests and biochemical analysis

Blood samples from each person were collected from the ante-brachial vein after they had been fasting for 8 to 12 hours. For this experiment, 7 mL of blood were placed in the clot tubes. After centrifuging serum samples at 4°C for a period of 10-15 minutes, they were stored at -70°C for later bioanalysis. OPN serum levels were determined using the ELISA kit (Biokit, China).

Dietary Inflammatory Index calculation and dietary assessment

Adult subjects were selected using a semi-quantitative, countrywide, validated 118-item food frequency questionnaire (FFQ) survey that contained precise and thorough dietary information (Mirmiran *et al*., 2010) Using in-person interviews, certified dietitians conducted this study, which included a list of products and the typical serving size for each food item. Participants reported the frequently of consumption for each food iteedm on a daily, weekly, monthly, and annual basis.

household dimensions (Ghaffarpour *et al*., 1999) an adjusted version of the NUTRITIONIST IV software (version 7.0; N-Squared Computing, Salem, OR, USA) for Iranian cuisine were used to convert and calculate the consumed meal sizes to grams.

We used of the method developed by Shivappa *et al*. to calculate the DII (Shivappa *et al*., 2014). Data on 21 dietary components, including protein, fat, carbs, calories, legumes, fibers,e whole grains, vegetables, fruits, cholesterol, dairy, processed meat, oils, sugar, nuts, and vitamins (D, E, K, A, C, and B12) were collected for this study. In the study by Shivappa *et al*., the DII score was derived using published adjusted scores (Anand *et al*., 2022). The scores for the total inflammatory effects were multiplied by the intake for every subject. The results for each dietary component were then combined. The DII score increases as the diet becomes more pro-inflammatory. Negative values indicate a more anti-inflammatory diet.

SALT Score

The severity of Alopecia Areata (AA) was evaluated using the severity of the alopecia tool (SALT) score (Olsen & Canfield, 2016). Patients with AA were separated into two groups based on SALT scores: moderate to severe (≥25) and mild (<25).

For those that have a SALT score of 25 or higher a steroid mini pulse therapy is recommended by the Japanese Dermatological Association (Ito, 2012).

Data Preprocessing and Feature Engineering:

A vital first step was to perform data preprocessing to attain data quality and ready the dataset for effective model training. This required a significant amount of cleaning, for example, removing duplicate rows (by using pandas. DataFrame. drop_duplicates to eliminate bias), corrupted data (detected with out-of-bounds values and either corrected or removed), and missing data (numerical columns imputed with mean values, and categorical columns imputed with a mode based on data distribution). In order to improve model accuracy and performance, for categorical variables, one-hot encoding was used (numerical representation suited for algorithms), the numerical data were standardized using Standard Scaler (Transforms features by removing the mean and scaling to unit variance, which is suitable for algorithms that are sensitive to the scaling of features, such as KNN). Dimensionality reduction, using Principal Component Analysis (PCA), was also a step in the process to filter out the features that were the most informative.

Due to the dataset being relatively small, the use of PCA was crucial to reduce the size of the feature set and minimize multicollinearity and redundancy. Although our sample size is enough to be trained by many models, for our use case, the large number of features relative to the data set might have led to over-fitting, which will make the model more difficult to train. PCA helped in identifying the most important pattern in the data and removing less important and nosy features. Using PCA made the model faster and more efficient while being better at handling new data by highlighting the most important features. Through the careful selection of key features to keep, the authors were able to simplify the data while making sure to keep all the important information.

Model Development and Evaluation:

In this study three machine learning classifiers were used, Random Forest, Logistic Regression, and KNN. We used Grid Search Cross-Validation (GridSearchCV) to perform a hyperparameter optimization on various hyperparameters to tune the Random Forest model. We experimented with various values of n_estimators (from 100 to 500, with 50 points apart), max_depth (from 5 to 20, with 5 points apart), and min_samples_split (from 2 to 10). In our tests, it was found that n_estimators=300, max_depth=15, and min_samples_split=5 provide better options to minimize out-of-bag error.

In the case of the Logistic Regression model, we used L2 regularization to avoid overfitting. The regularization parameter C was optimized using 5-fold cross-validation, where a C value of 0.01 score the average highest mean AUC score across all folds.

For creating the KNN model, we chose 7 neighbors since that was the number with the least validation error after a 10-fold cross-validation. Before training the model, we ran PCA for feature space reduction. Through the elbow method, we kept 15 principal components, which corresponded to 90% of the variance in the data.

To evaluate the performance of each model, we calculated multiple metrics, namely accuracy, precision, recall, F1 score, and AUC score, over a held-out test set consisting of 20% of the data. Moreover, we constructed confusion matrices and classification reports to understand in greater detail how the models performed, with a special focus on potential biases and class-specific performance.

Machine Learning Tools:

To develop and evaluate the models, various machine-learning tools and libraries were employed, including scikit-learn (sklearn v1.4.2) (*Buitinck et a*l., 2013). Other libraries like Matplotlib (v3.9) and Seaborn (v0.13) were used for data visualizations, such as correlation matrix heat maps, ROC curves, partial dependence plots (PDPs), etc. For data handling and manipulation Pandas was additionally utilized.

Machine Learning Classifiers:

Machine learning classifiers upon which this study is based are Random Forest Logistic Regression. It includes the k-Nearest Neighbours (KNN). As the name suggests, Random Forest is an ensemble of decision trees, each of which is trained on a subset of data, using a random subset of the features, which leads to reducing the correlation among trees and thus more enhanced performance and accuracy (Parmar *et al*., 2019). Meanwhile, logistic Regression calculates and then predicts the probability of an event occurring or not, such as the likelihood of a person voting or not using a set of independent variables. It is also commonly known as logit model, this statistical model is widely used in classification where the outcome is a value between 0 and 1 (Pranckevičius & Marcinkevičius, 2017). However, KNN is a supervised, non-parametric classifier that measures the distance between data points based on their closeness to one another. Although KNN can be used in both classification and regression, it is mainly used for classification, operating under the premise that similar data points are located near each other (Abu Alfeilat e*t al*., 2019).

Model Interpretation and Deployment:

For a better understanding of the influence of each feature and its relationship to the outcome, a model interpretation was performed, and Partial Dependence Plots (PDP) were plotted to determine the impact of each feature and its likelihood of causing alopecia. Furthermore, to find out the correlation strength between each feature and the outcome, Pearson correlation coefficients (r) were calculated. However, this study does not have a deployment stage at this point, as our main focus was on model development evaluation.

3. RESULT:

The main goal of this research was to use machine learning models to investigate the relationship between the DII and the prevalence and severity of alopecia areata (AA). The authors of this study used a diverse set of classifiers that included Random Forest, Logistic Regression, and K-Nearest Neighbors (KNN) to evaluate the prediction capabilities of each model for AA severity as measured by the Severity of Alopecia Tool (SALT) score. Additionally, the study aimed to determine whether dietary patterns with higher pro-inflammatory potential, as measured by the DII, were associated with an increased risk of developing AA and greater disease severity.

The machine learning models performed exceptionally well in predicting the existence and severity of AA based on the different performance criteria listed in Table 1 and Figure 1 for each model.

Table 1: Models' Performance.

	Accuracy %	Precision %	Recall %	F1 score %	ROC AUC score %
Random Forest	98.77	98.35	98.8	98.7	98.73
Logistic Regression	98.64	98.29	98.85	98.64	98.65
KNN	98.1	98.93	98.56	98.14	98.34

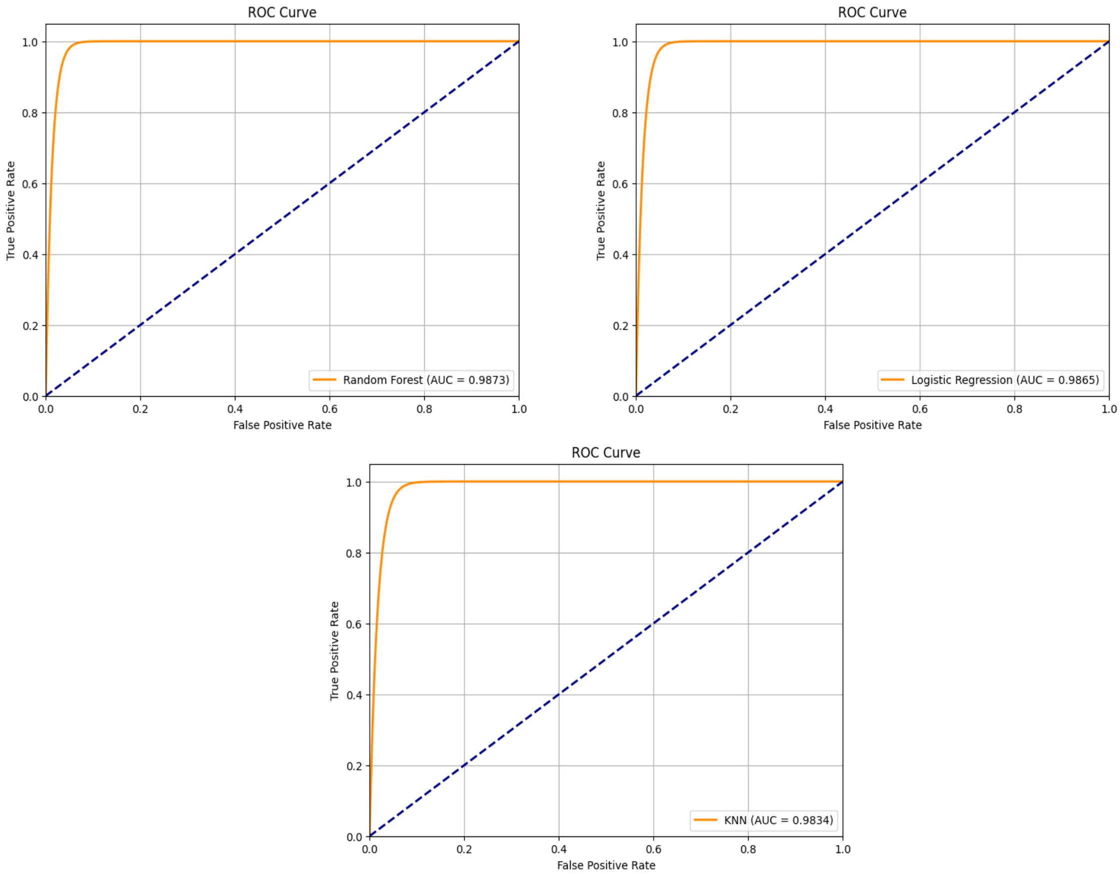

Figure 1: Receiver Operating Characteristic (ROC) Curves for Random Forest, Logistic Regression, and K-Nearest Neighbors (KNN) Models. The ROC curves illustrate the performance of three classification models by plotting the True Positive Rate (Sensitivity) against the False Positive Rate. The Area Under the Curve (AUC) values indicate the discriminatory ability of each model. The Random Forest model achieved the highest AUC (0.9873), followed closely by Logistic Regression (0.9865) and KNN (0.9834). Higher AUC values suggest better model performance in distinguishing between positive and negative classes. The dashed diagonal line represents the performance of a random classifier (AUC = 0.5).

These findings demonstrate the efficacy and usefulness of machine learning in investigating the relationship between dietary inflammatory index (as measured by the DII) and the presence and severity of AA. In this study, data from 427 males and females between the ages of 42 and 64 were evaluated. According to dietary inflammatory index tertiles, data were collected from each participant based on the following variables: DII score, Age, BMI (kg/m2), WHR (waist-hip ratio), SALT score, OPN ng/dL, Gender (Male, Female), Marital status (Married, Single, Widowed, Divorced), Socio-economic status (1(lowest),2, 3(highest)), Physical activity (Met-h/day) (Light, Mo derate, High).

Figure 2 reveals a compelling association between dietary habits and the incidence of alopecia, highlighting on factors that may influence the development of this condition. Participants who incorporated higher quantities of nuts, fruits, fibers, proteins, carbohydrates (CHO), and dairy into their diets had a significantly lower likelihood of experiencing alopecia. Conversely, those individuals whose diets were characterized by an increased consumption of vegetables, grains, fat, sugar, processed meats, and oil demonstrated a higher susceptibility to alopecia. These findings underscore the potential impact of specific dietary choices on hair health, suggesting that a well-balanced diet rich in certain nutrients may act as a protective factor against alopecia. Further research and lifestyle interventions are needed to better understand and harness the preventive potential of dietary modifications in addressing alopecia

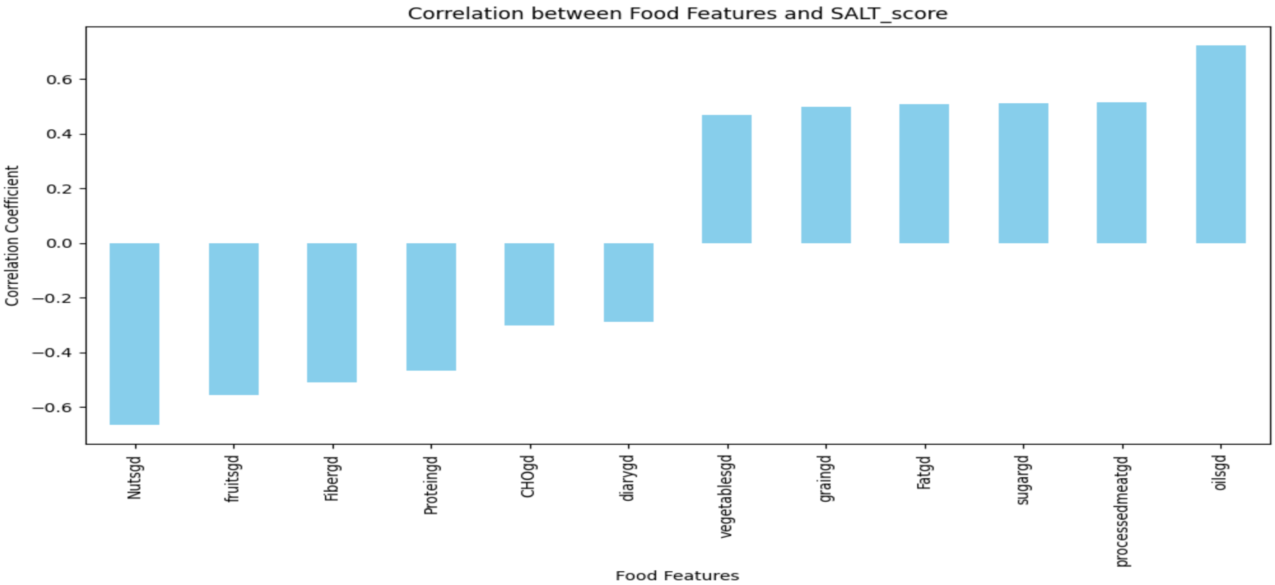

Figure 2: Partial Dependence Plots (PDPs) visualizing key dietary factors associated with the predicted risk of AA. Each plot indicates the marginal effect of a given dietary component on AA risk, while keeping other variables constant.

As evident in figure 3, the partial dependence plot provides insights into the determinants that affect the predicted response of a machine learning model with respect to alopecia. Older Age and higher BMI are positively correlated with AA, which is to say that the chances of developing alopecia increase with aging and with increased BMI. Moreover, higher intakes of oil, fat, and grains also appear positively associated with alopecia, indicating that high levels of these dietary components could be related to a higher risk of hair loss. By contrast, the plot suggests a negative correlation with some key variables that could reflect some protective effects of certain nutrients. A high intake of vitamins C, B12, K, E, D, and A, and nuts is associated with a decreased risk of alopecia. indicating that a diet that includes these essential nutrients is necessary for healthy hair. The discoveries offer not only help in understanding the complex relationships between these lifestyle factors and alopecia but pave the way for target-driven preventative treatments as well.

Figure 4 shows a correlation heatmap for nutrition factors and their link to alopecia, which provides valuable insights into the complex relationship between dietary ingredients and the chance of developing hair loss. The data shows some noteworthy patterns, individuals who consume higher amounts of essential vitamins, such as C, B12, K, D, and A, as well as nuts as we mentioned about in previous paragraph, as well as fruits, and legumes, had a lower risk of getting alopecia. The data shows the possible benefits of a diet rich in certain nutrients for hair health. In contrast, older age, higher body mass index (BMI), and higher caloric intake were all shown to have a positive correlation with an increased risk of alopecia. This information not only improves our understanding of the complex nature of alopecia, but it also indicates a possible path for preventative measures and therapies that target certain dietary components to reduce the risk of hair loss.

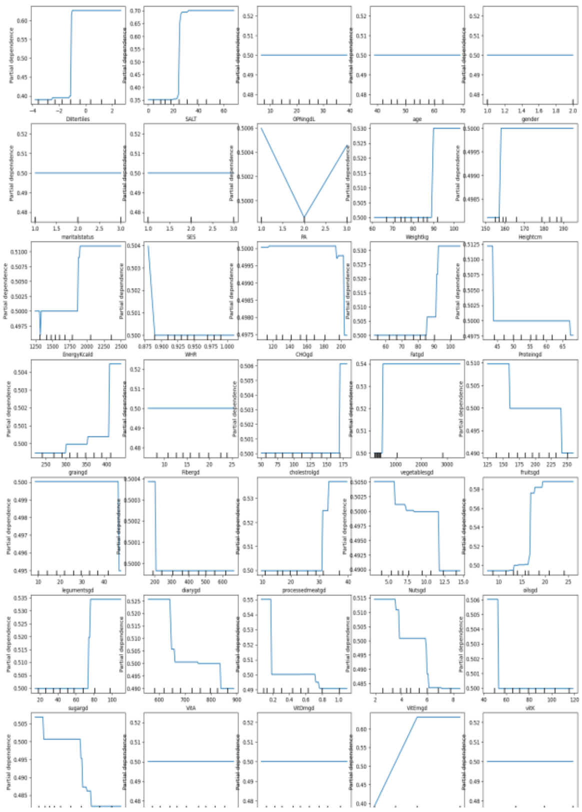

Figure 1: Partial Dependence Plots (PDP) for Each Feature.

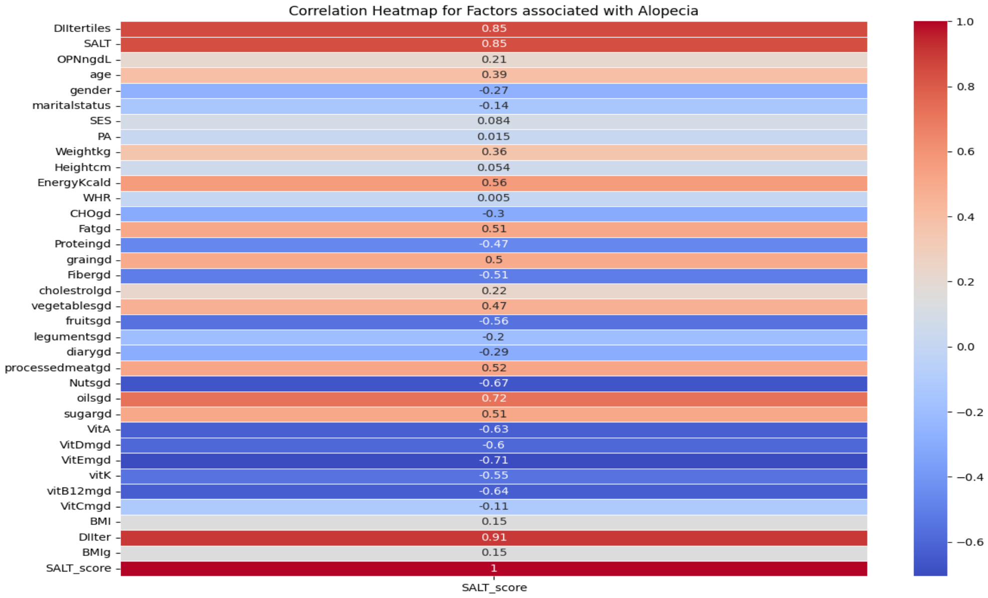

Figure 4: Correlation Heatmap for Factors Associated with Alopecia

4. DISCUSSION:

As far as we are aware, this is the first study to use machine learning models are being utilized in a research paper to investigate the relationship between DII and AA. The machine learning models developed by the authors were highly accurate and performed very well in predicting the link between Dietary Inflammatory Index (DII) and alopecia areata (AA). The Random Forest model, after hyperparameter tuning, achieved an accuracy of 98.77% on the validation set, demonstrating its ability to handle complex datasets. With the incorporation of L2 regularization to reduce over-fitting, our Logistic Regression model achieved an accuracy of 98.64% on the validation set, showing its effectiveness as a classifier. In addition, the KNN model, using PCA for dimensionality reduction, achieved an accuracy of 98.10%, proving that models in this domain can learn these complex patterns.

Our findings align with previous research (Alanazi, 2022; Šín *et al*., 2022), supporting the reliability of machine learning (ML) models in predicting clinical outcomes. Despite achieving higher accuracy in predicting alopecia severity, our study reinforces the utility of ML across medical conditions. We also highlight the importance of data pre-processing, including feature engineering, PCA for dimensionality reduction, and one-hot encoding, which have proven effective in enhancing model performance (Salih & Pasha, 2024; Verma *et al*., 2020)

Despite our models performing well (good predictive analysis of the data), we also have some other things to consider including the restrictions of each model. For example, even though Random Forest had the highest accuracy and other models were outperformed, its complex, ensemble structure inherently limits its ability to provide clear, feature-level insights, thus hindering interpretability. This high performance might come at the cost of transparency, which might be very problematic in the field of healthcare. Meanwhile, although the Logistic Regression model achieved as high an accuracy as Random Forest, its simpler design and its reliance on regularization might hinder its ability to detect complex correlation between the data. As for the KNN, it performed like the other two models but it benefited from PCA for dimensionality reduction. However, KNN's use of distance metrics can become less efficient as the data's dimensionality increases, likely resulting in decreased performance with more complex datasets.

Moreover, while the models achieved high accuracy in the validation set, they have not been tested in actual clinical environments, which may introduce new challenges, such as handling noisy or imbalanced data. Another limitation of the study is the use of a single dataset, which may limit the applicability of the findings to other groups or environments. Future studies should focus on testing these models on external datasets to evaluate their performance and address potential overfitting

The findings of this paper support the efficacy of machine learning models in predicting the severity of alopecia areata. Our findings contribute to the ever-expanding body of data supporting the application of machine learning in healthcare, highlighting the importance of data preprocessing, feature engineering and various other model optimization methods in achieving high prediction accuracy.

The observed correlations between dietary patterns and alopecia risk highlight the importance of understanding lifestyle factors in disease development and progression, emphasizing the intricate relationship between dietary habits and alopecia occurrence in our study. Participants with higher DII, which corresponds to diets with higher proinflammatory potential, had a higher risk of developing AA than participants with lower DII, indicating anti-inflammatory diets. Additionally, significant differences were observed in the dietary categories and nutrients consumed in the tertiles of DII. Due to its impact on hair follicles, AA is an autoimmune illness that results in hair loss. Despite the fact that its precise cause has not yet been found. Alopecia areata (AA) is an autoimmune disease that leads to non-scarring hair loss, often appearing as patches on the face, scalp, and other body areas (Gilhar *et al*., 2019).

One of the environmental factors that influences the development of AA is nutrition, an individual's diet can affect their immune system and hair follicles, which might contribute to the development of AA (Thompson *et al*., 2017). A Western diet high in sugar, fat, salt, and low in fiber was suggested to promote the estart and progression of severe autoimmune disorders.

A significant correlation between higher DII scores and AA risks was found in the overall analysis of the present investigation. Although the relationship between the DII score and AA risk has not been studied; nonetheless, our results are comparable with those of other studies on the relationship between the DII and autoimmune disease occurrence (Hajianfar *et al*., 2022). Additionally, the DII scores in our study were consistent with those from past research (Shivappa *et al*., 2014, Shivappa *et al*., 2018). The DII based on our FFQ and applied to the population of our study appears to be sufficient for this sort of assessment and explanation of the results of prior results. Therefore, research is necessary to examine the connections between AA risks and DII scores. Based on this study we came to the conclusion that AA is associated with a low DII score. In this sense, it appears that eating habits with low DII scores may prevent the onset of AA. In this study, we demonstrated that participants with baldness consumed more calories with higher fat content than persons without AA. Additionally, young males with baldness had considerably higher diastolic blood pressure while having much lower HDL-C levels (González-González *et al*., 2009). A Turkish study involving young male volunteers found that the AA community had significantly higher levels of MetS components including blood pressure and total cholesterol (Mumcuoglu *et al*., 2011). Inflammation caused by a diet heavy in processed carbs added sugar, and increased sugar can lead to weight gain and insulin resistance (Bosma-den *et al*., 2012). Inflammation and insulin resistance (IR) are pathogenic variables in AA (Matilainen *et al*., 2003). Studies show that AA may be a sign of metabolic disorders such as elevated insulin resistance, total cholesterol, triglycerides, reduced insulin sensitivity, and low HDL-C (Cakir, 2013). An expanding amount of evidence links elements of metabolic syndrome to hair loss. Early androgenic alopecia in men has been linked to IR, which is a sign of metabolic syndrome (Matilainen *et al., 2*000).

However, multiple studies have revealed a significant association between DII and serum inflammatory markers (Cavicchi*a et al., 2009, Kaluza et al., 2018, Shin et al., 202*0). Similar to our findings, Italian longitudinal research found that bread consumption was higher among individuals in the top quartile of the DII (Shivappa *et al.*, 2015). Refined grain consumption was associated to higher levels of inflammatory markers (Masters *et al*., 2010, De Punder *et al.*, 2013). Therefore, this finding will likely be verified in populations who regularly consume substantial amounts of refined grains. We found that individuals who score lower on the DII consume more fruits and vegetables. Inflammation and fruit and vegetable consumption were incompatible (*Holt et al.,* 2009). When calculating the DII, several of nutrients that are abundant in vegetables and fruits, like dietary fiber, have a poor total inflammatory impact score (Azadbakht & Esmaillzadeh, 2009). Therefore, greater consumption of vegetables and fruit eating was expected among participants with lower DII score.

In comparison, Previous studies have shown that consumption of full-fat dairy products decreased inflammatory markers (Jenkins *et al.*, 2003). According to the results in Figure 1, those how consumed more meat had a higher inflammatory marker which is aligned with prior studies that found red meat consumption elevated inflammatory marker levels (Azadbakht & Esmaillzadeh, 2009, *Samraj et al*., 2015). However, the relationship between certain dietary factors and inflammation is complex, and results vary. Our findings, for instance, indicate a positive correlation between red meat consumption and inflammation, but other studies have shown weaker correlations (Wood *et al*., 2023) probably related to factors such as the way meat is prepared or the body weight of individuals. These results may also inspire future clinical studies to further enhance the understanding of this complex interplay between diet and inflammation.

Consumption of retinol (vitamin A1) was linked to the SALT score. These findings imply that increased retinol consumption may exacerbate AA by increasing the active retinol metabolite, retinoic acid (RA). Retinoic acid could potentially increase the susceptibility of hair follicles to attack by NKG2D+ effector cells using signaling to stimulating the entrance of hair follicle stem cells into growth phase through the integration site family of wingless-type mouse mammary tumor virus(Suo *et al*., 2015). However, our data revealed a negative correlation between vitamin A and AA, since abundant intake of vitamin A was related to less severe AA. This gap suggests that there may be species-specific differences with respect to vitamin A regulation of AA and it merits further investigation.

According to our findings and other studies, a deficiency in micro-nutrients, like minerals and vitamins, may promote the growth of AA (Thompson *et al*., 2017), because people with AA often had decreased blood levels of zinc, vitamin D, and folate compared to healthy controls (Thompson *et al*., 2017). Excessive or insufficient amounts of vitamin A may promote AA development, according to certain studies (Duncan *et al*., 2013).

OPN, on the other hand, is known to be a factor that can be produced by some immune cells and could elevate in specific immune illnesses. Studies on the connection between AA and OPN shown that, similar to certain other inflammatory disorders, people with AA had higher blood levels of OPN. In case-control research by ((Ganzetti *et al*., 2015), they assessed the OPN blood levels in 40 patients receiving 3- and 2-diphenylcyclopropenone (DPCP) as part of an immunotherapy regimen before and 12 months after the commencement of the treatment, and 20 healthy persons were compared. According to the study's findings, OPN blood levels were noticeably greater in AA patients; however, there was no discernible decrease after taking DPCP (Ganzetti *et al*., 2015).

Researchers assessed the blood levels of OPN in AA patients and a control group for a separate study, the findings of this study revealed that AA patients' blood levels of OPN were considerably lower than those of the control group (Soheila *et al*., 2018). (Rateb *et al*., 2015) compared patients with AA that had their level of OPN tissues assessed by real-time PCR to that in the control group after examining OPN gene expression in individuals with alopecia areata and drawing that comparison (Rateb *et al*., 2015).

The SALT score and OPN serum level had a statistically significant connection in our study. SALT score and OPN mRNA expression in individuals did not significantly correlate in (Rateb *et al*., 2015) study. Additionally, (Soheila *et al*., 2018) found no correlation between OPN serum level and illness severity.

The current study has various advantages, including being one of the first studies to examine the relationship between dietary inflammatory index and alopecia areata in Iraq using machine learning methods. It also highlights a significant correlation between the two when confounding variables are taken into account. Even if there are some limitations, DII could have certain restrictions related to dietary plans. Out of the 45 dietary components, only 21 FFQ items were accessible for computing DII, meaning some dietary components may have been unaccounted for. The study was cross-sectional; hence, it is difficult to determine the phenomenon's cause.

Limitations and Future Directions:

The main limitation of our study is the small dataset size, which may limit the generalizability of our findings. The small dataset may impact the model's capacity to capture the complete spectrum of factors influencing the association between dietary patterns and alopecia areata. Future studies should involve larger, more diverse datasets and employ more sophisticated machine learning techniques or ensemble models to improve prediction accuracy. Furthermore, combining biomarkers or genetic data with dietary information may offer a more extensive understanding of the underlying processes that link nutrition, inflammation, and AA.

CONCLUSION:

Our study found a significant relationship between dietary patterns with higher pro-inflammatory potential and an elevated risk of alopecia areata (AA), especially in the elderly. Using machine learning models optimized with various techniques allowed us to predict the severity of AA based on dietary inflammatory patterns. These findings show the complex relationship between dietary habits, inflammatory diets, and the likelihood of AA occurrence, highlighting the need to use machine learning tools for predictive analysis in healthcare. However, more cohort studies are required to confirm these findings and thoroughly understand the underlying mechanisms that govern the relationship between AA and dietary inflammation.

DECLARATIONS:

Ethical approval and participant consent

This study was approved by the Ethics Committee of Garmian Polytechnic University, Kalar Technical Institute wth Code Number: GPUREC03924; 19/09/2024. All methods were implemented according to guidelines and regulations. Oral and written informed consent were provided to all the participants. The Declaration of Helsinki carried out this research.

Publication consent

Does not apply.

Data availability

The data used in this study are available from the corresponding author on request.

Conflicts of interest

The authors have no conflicts of interest to declare.

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Authors' contribution

Mohammed Sarwat and Hawal Lateef designed the study. Mohammad Sarwat developed the machine learning models and analyzed the data. Mohammed Sarwat, Hawal Lateef, Soran Pasha, and Hassan Tawfiq prepared the manuscript draft.

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