Squeezenet-based Image Classification and Prediction of High Frenal Attachment in the Upper Lip

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KEYWORDS
High frenal attachment, machine learning, lip, Logistic Regression.

ABSTRACT

Background & Aim: Traditional methods like clinical examinations and the Graber test have been used to assess abnormal frenula. Still, machine learning offers a quantitative and data-driven methodology to explore the intricate relationship between frenulum variations and their potential consequences. These attachments are linked to age, gender, and oral hygiene. Midline labial frenulum (MLF) abnormalities are common in preschoolers but diminish with age. AI can improve dentistry by predicting and classifying frenum attachments using machine learning algorithms, computer vision tools, big data analysis, predictive analytics, automation, workflow enhancement, and training. Deep learning algorithms can classify attachment types on large datasets, while computer vision tools can efficiently analyze images for specific features. This study aims to explore the predictive modeling and classification of high frenal attachment in the upper lip using machine learning algorithms.

Material and Methods: We collected 180 radiographic image samples, leveraging an institutional computational database. We employed a robust predictive model using the SqueezeNet architecture for image embeddings and subjected to Naive Bayes and Logistic Regression algorithms. The dataset, containing 90 samples with and 90 without high frenum, underwent preprocessing, customization, and division for training and testing. Performance evaluation involved metrics such as AUC, Classification Accuracy, F1 Score, Precision, and Recall.

Results: The Naive Bayes model demonstrated a remarkable AUC of 0.998, while Logistic Regression exhibited perfection with an AUC of 1.000. Both models showcased high Classification Accuracy (Naive Bayes: 0.971, Logistic Regression: 1.000) and balanced F1 Scores. Precision and Recall metrics reinforced the models' accuracy in positive predictions and capturing positive instances.

Conclusion: Our results signify the potential clinical utility of machine learning algorithms in predicting high frenal attachment. Despite limitations, these findings pave the way for enhanced diagnostic capabilities in orofacial anatomy, emphasizing the need for continued research and refinement of predictive models for broader applications

1. Introduction

The upper labial frenulum, a mucosal attachment within the oral cavity, has emerged as a subject of profound scientific inquiry. Often overlooked, this small frenum is critical in stabilizing the upper and lower lips and the tongue, influencing both functional and aesthetic aspects of orofacial anatomy. (1) Traditional methods, such as clinical examinations and the Graber test, have long been employed to assess abnormal frenula. However, introducing machine learning algorithms signifies a paradigm shift, providing a quantitative and data-driven methodology to explore the intricate relationship between frenulum variations and their potential consequences. (2,3) A recent study involving 380 Nepalese dental patients (4) found that maxillary and mandibular frenal attachments were prevalent among them, with gingival attachments in the maxilla and mucosal attachments in the mandible. A recent study found significant correlations between frenal attachments and age, gender, and oral hygiene, with normal frenum being the predominant variation. A review of the literature on midline labial frenulum (MLF) abnormalities reveals that they are common in preschoolers but diminish with age (3,5). The relationship between MLF frenectomy and breastfeeding outcomes is controversial, with clinical appearance not necessarily correlated with functional breastfeeding issues. Surgical techniques have evolved from traditional scalpel methods to laser-assisted procedures, but further research is needed to refine diagnostic criteria and treatment protocols for MLF abnormalities in pediatric patients.

Predicting and classifying frenum attachments in dentistry, particularly labial and lingual frenulum, is crucial for clinical practice and patient care. The importance of this is evident in the impact on oral function, orthodontic considerations, treatment planning, prevention of complications, patient education and counseling, and research and development (3). AI can aid in prediction and classification by using machine learning algorithms, computer vision tools, big data analysis, predictive analytics, automation and workflow enhancement, and training and education. Deep learning algorithms can be trained on large datasets of oral photographs to classify different types of frenal attachments accurately. Computer vision tools can efficiently analyze images to detect anatomical features and accurately classify attachment type (6,7).

AI-powered tools can automate the initial screening and classification process, allowing healthcare professionals to allocate time for more critical aspects of care. AI applications can be integrated into existing dental software systems to provide real-time analysis and support during patient evaluation (6). AI can revolutionize dentistry by improving diagnostic accuracy, patient outcomes, and treatment planning. It can be integrated into daily dental practice, streamlining workflows and providing data-driven insights, ultimately leading to better oral health care. (7)Frenal attachments, a small fold of tissue connecting the lip to the gums or the tongue to the floor of the mouth, are crucial in dentistry and orthodontics. Classifying these attachments can help diagnose and plan treatment for patients with concerns related to these structures. A recent study employs SqueezeNet to analyze mammography images, enhancing the accuracy and sensitivity of a support vector machine making it a promising option for early breast cancer detection (8).

Machine learning algorithms are ideal for classifying frenal attachments due to their automation, high throughput, and consistency. SqueezeNet embeddings (9) and these algorithms are particularly useful for applications on devices with limited computational resources. Feature extraction using SqueezeNet involves loading the pre-trained model and extracting embeddings from frenal images. Classifier training involves selecting and implementing machine learning algorithms, training models, and evaluating performance. SqueezeNet embeddings and algorithms can improve dental and orthodontic diagnosis and treatment planning. The classification system, including mucosal, gingival, papillary, and papilla-penetrating attachments, is the foundation for this analysis. Machine learning algorithms are adept at discerning patterns and associations within these classifications, providing a sophisticated and objective lens to understand the diversity of frenal anatomy (10) In contrast to previous research, this study sheds light on the potential clinical implications of abnormal frenal attachments, transcending traditional diagnostic approaches. The utilization of machine learning not only offers enhanced diagnostic accuracy but also facilitates a deeper understanding of the intricate interplay between anatomical variations and clinical outcomes. (11)

As we explore frenulum anatomy, it is crucial to acknowledge the transformative potential of machine learning in oral healthcare. By bridging traditional clinical knowledge with cutting-edge technology, this study aspires to contribute valuable insights to the scientific community, pushing the boundaries of our understanding of orofacial anatomy and offering a foundation for future research and clinical applications. Ultimately, this study aims to predict and classify the various high frenal attachments using AI algorithms.

1.1 Methods

One hundred eighty radiographic image samples were obtained for this study, sourced from the literature search and the computational database portal of Saveetha Dental College. The dataset consisted of 90 samples with and without 90 samples of frenal attachment. Data preprocessing was conducted to customize and categorize the images into distinct groups. Ethical approval was deemed unnecessary as the data were sourced from a computational database spanning 2019 to 2023, and dental professionals verified the authenticity of the images.

To investigate the prediction accuracy, the orange machine learning framework (version 17) was employed, utilizing a SqueezeNet embedding model and subjected to Naive Bayes and Logistic Regression algorithms classification of embeddings. (12) The dataset was partitioned, with 80% for training and 20% for testing. (fig-1)

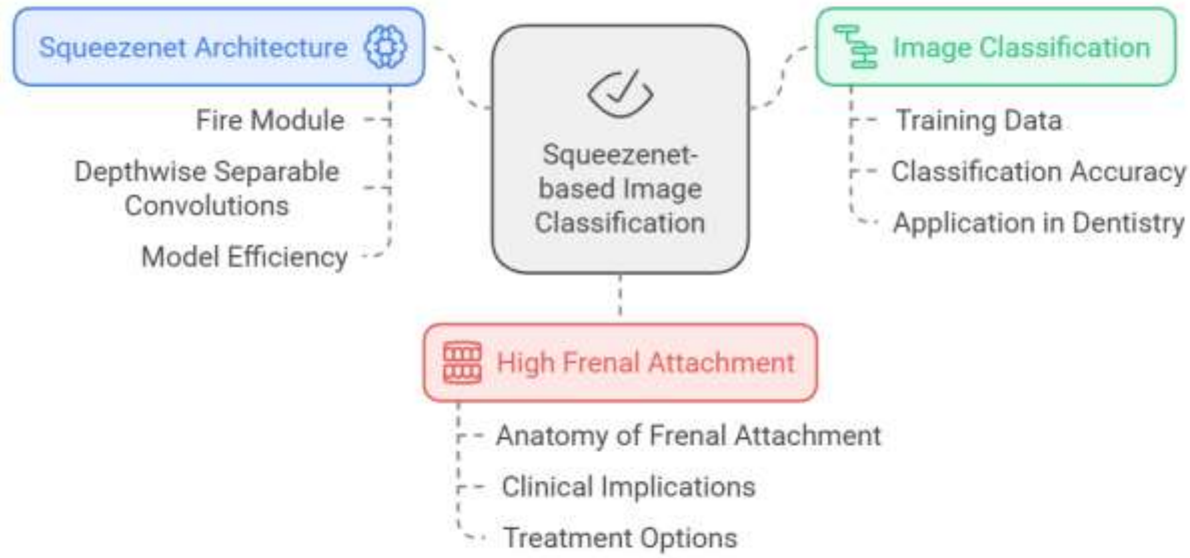

Fig. 1: shows the workflow diagram.

1.2 Squeezenet architecture

The SqueezeNet architecture (9,13) for image classification comprises several essential components. The input is processed through an initial convolution layer with a 7x7 filter and a stride of 2, followed by a Rectified Linear Unit (ReLU) activation function, effectively reducing the spatial size of the input. (14) The core building blocks of SqueezeNet are the "fire" modules, consisting of squeeze and expand layers. The squeeze layer employs 1x1 convolutions to reduce input channel dimensions, optimizing feature compression. The expand layer includes parallel paths with 1x1 and 3x3 convolutions, enhancing channel count and spatial coverage. The outputs from these paths are concatenated along the channel dimension. Downsampling is achieved through max-pooling layers with a stride of 2, strategically placed to minimize feature map dimensions while retaining crucial information. The network concludes with a global average pooling layer, generating a fixed-size feature vector. This is succeeded by a fully connected layer with softmax activation for final classification. Following image embedding, the dataset underwent analysis using machine learning algorithms, specifically Naive Bayes and Logistic Regression, to discern patterns and relationships within the dataset. (fig-2)

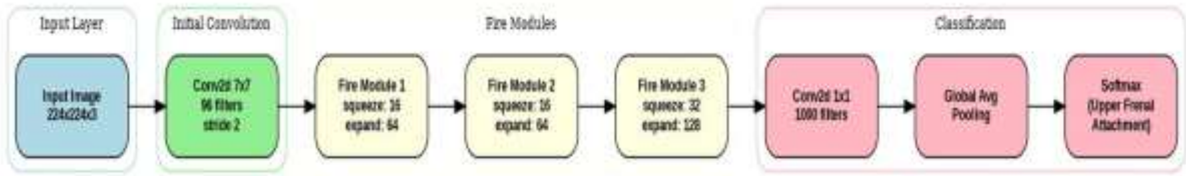

Fig. 2: Squeeze net architecture with image classification

1.3 Logistic Regression architecture

Logistic Regression is a statistical method used for binary classification problems to predict the probability of an input belonging to a specific category. It uses multiple input features, continuous or categorical, and a dataset with labeled examples for training. The model forms a linear combination of these features using weights learned during training. The sigmoid function converts the linear combination into a probability, with a value between 0 and 1, representing the probability that the input belongs to the positive class. The output probability can be thresholded to classify the input into one of the two classes. The weights are optimized using gradient or stochastic gradient descent to minimize the loss function.

1.4 Naive Bayes

Naive Bayes is a probabilistic algorithm based on Bayes' theorem, specifically designed for classification tasks. It takes several input features and can handle continuous and categorical data. The core of Naive Bayes is Bayes' theorem, which updates probability estimates as new information becomes available. The "naive" part of the algorithm assumes that all feature variables are independent of each other given the class label, allowing the likelihood to be decomposed. To classify a new instance, Naive Bayes computes the posterior probability for each class using the training data and selects the class with the highest probability. The training process involves estimating the prior probabilities and likelihoods from the training data, often using maximum likelihood estimation.

1.5 Evaluation metrics

The machine learning workflow evaluates model performance using metrics like Receiver Operating Characteristic (ROC) Analysis. ROC analysis is a graphical representation of a binary classifier system's diagnostic ability, plotting True Positive Rate (TPR) against False Positive Rate (FPR) at different thresholds. Key concepts include True Positive Rate (sensitivity) and False Positive Rate (false positive rate). Higher AUC values indicate better model performance.

Cross-validation is a statistical technique that assesses the generalizability of results to an independent dataset. It involves partitioning the original training set into subsets, training the model on some subsets, and validating it on others. Common methods include K-Fold Cross-Validation, which minimizes random variance in performance outcomes, and Stratified K-Fold Cross-Validation, which maintains dataset distribution proportions. A confusion matrix is a table that compares predicted and actual classifications of an algorithm, identifying True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). It provides metrics like accuracy, precision, recall, and F1 score. Recall, also known as sensitivity or True Positive Rate, measures the proportion of positive cases correctly identified by a model. This is crucial in critical scenarios like medical diagnoses or fraud detection. Precision, or Positive Predictive Value, measures the proportion of correctly identified positive cases, which is crucial in high-cost situations like spam detection or email classification. The F1 score is a metric that balances precision and recall, which is useful for dealing with imbalanced classes. It is calculated as 2 x \frac{Precision} x \frac{Recall}, providing a comprehensive assessment of model performance. Combining these metrics ensures the model is suitable for the intended application and real-world deployment.

2. Results

The Naive Bayes model demonstrated a remarkable Area Under the Curve (AUC) of 0.998, indicating its strong discriminatory ability. The model achieved a high Classification Accuracy (CA) of 0.971, suggesting that approximately 97.1% of instances were correctly classified. Additionally, the F1 Score, a measure of the balance between precision and recall, was 0.971, highlighting the model's ability to maintain equilibrium between false positives and false negatives. Precision, measuring the accuracy of positive predictions, was 0.973, while recall, assessing the model's ability to capture all positive instances, was 0.971. These results collectively underscore the Naive Bayes model's robust performance, indicating its accuracy and reliability in predicting upper frenum

On the other hand, the Logistic Regression model exhibited outstanding performance across all evaluated metrics. It achieved a perfect AUC of 1.000, signaling flawless discriminatory ability. The model's Classification Accuracy (CA) was also perfect at 1.000, indicating that all instances were correctly classified. Furthermore, the F1 Score, precision, and recall all registered at a perfect 1.000, underscoring the model's exceptional predictive accuracy and precision. These results highlight the Logistic Regression model as highly effective in predicting and classifying upper frenum, suggesting its potential utility in clinical applications related to identifying such dental conditions.

Table 1: Accuracy of algorithms of Naive Bayes and Logistic Regression

Model	AUC	CA	F1	Precision	Recall
Naive Bayes	0.998	0.971	0.971	0.973	0.971
Logistic Regression	1.000	1.000	1.000	1.000	1.000

Table -1 compares the performance of Naive Bayes and Logistic Regression models in classifying upper frenal attachments. The models are evaluated using AUC, CA, F1 Score, precision, recall, and recall metrics. Naive Bayes has a high AUC of 0.998, indicating excellent discrimination, while Logistic Regression has an AUC of 1.000, indicating perfect classification ability. CA measures the proportion of true results among the cases examined, with Naive Bayes correctly classifying 97.1% of cases. F1 Score is the harmonic mean of precision and recall, with Naive Bayes having an F1 score of 0.971 and Logistic Regression having an F1 score of 1.000. Precision measures the accuracy of positive predictions, with Naive Bayes having a precision of 0.973 and Logistic Regression having a precision of 1.000. Recall measures the ability of the model to identify all relevant instances. Naive Bayes has a strong performance, but its precision and recall may be slightly lower. Logistic Regression outperforms Naive Bayes in all metrics.

Fig. 1: and 2 shows the roc value of the naives bayes and logistic regrsssion of the model

3. Discussion

Upper frenal attachments (15,16), particularly labial and buccal frenula, are crucial for dentists due to their impact on oral health, orthodontic planning, denture and restorations, speech therapy, pediatric dentistry, aesthetics, and periodontal surgical considerations (17). Anomalies or tight attachments can limit lip and cheek mobility, potentially affecting speech, mastication, and oral hygiene. Abnormal frenula can also lead to periodontal issues, especially in the labial frenum (18,19).

In orthodontics, understanding frenal attachments is crucial for space, alignment, and long-term retention strategies. In restoration dentistry, frenal attachments must be assessed to prevent irritation to gingival tissue around restorations (15,16,20,21). In speech therapy and pediatric dentistry, understanding frenal anatomy can help in cases of breastfeeding difficulties. Understanding upper frenulum attachments is crucial for dentists to provide comprehensive care that considers functional, aesthetic, and health-related factors in patients. Understanding and predicting these attachments helps plan surgical interventions and ensure optimal patient outcomes during examinations.

This study's results show impressive AUC values obtained for both the Naive Bayes (0.998) and Logistic Regression (1.000) models from squeeze net embeddings, indicating their high capacity for distinguishing between various types of frenal attachments, which is similar to a recent study SqueezeNet based spatial redundancy with 1 × 1 convolution kernels and Fire modules improves accuracy and computational efficiency by pooling feature maps and sharing information for LIDAR data. The Naive Bayes and Logistic Regression models have high Classification Accuracy (CA) and F1 Score, respectively, indicating their effectiveness in real-world scenarios. The Naive Bayes model has a high precision of 0.973 in positive predictions, while the Logistic Regression model has a perfect 1.000. These high accuracy levels highlight the models' robustness and ability to accurately classify instances of high frenal attachments, ensuring their effectiveness in real-world scenarios. (table-1)

The SqueezeNet architecture (22,23) employed in image embedding proved to be an effective feature extraction and classification tool. Its utilization of fire modules, incorporating squeeze and expand layers, enables the model to capture complex patterns within the frenal images. The downsampling technique, achieved through max-pooling layers, contributes to the reduction of spatial dimensions while preserving critical information, facilitating efficient image classification similar to the study showcases a novel AI method, SqueezeNet, aimed at enhancing COVID-19 diagnosis accuracy by utilizing superior data and settings compared to traditional chest X-ray methods (22,24).

These findings collectively underscore the potential of machine learning algorithms, Naive Bayes, and Logistic Regression in advancing diagnostic capabilities in dentistry. These models' high predictive accuracy and discriminatory ability suggest their applicability in clinical settings for the precise identification and classification of high frenal attachments. As we navigate the intersection of traditional clinical knowledge and cutting-edge technology, these results pave the way for further research and implementation of machine learning in frenal anatomy and pathology, promising enhanced diagnostic accuracy and improved patient outcomes.

Naive Bayes and Logistic Regression models(fig-1,2) are effective in upper frenal attachment diagnosis but have limitations such as feature independence, sensitivity to imbalanced data, lack of temporal data, limited generalizability, overfitting concerns, and interpretation of metrics. It should expand datasets, incorporate additional features, use advanced algorithms, and conduct real-world testing to improve their generalizability. Further analysis of clinical relevance and decision-making impact is needed to enhance these models' clinical utility literature, affirming the reliability of identified predictors for high frenal attachment across diverse populations yet acknowledging potential discrepancies rooted in sample variations and methodological nuances. Establishing a predictive model and classification system holds immediate clinical significance, enabling targeted interventions to address functional challenges and aesthetic concerns. However, limitations include reliance on a computational database, potential biases, and a retrospective design. Future research should diversify datasets, employ prospective study designs, explore additional algorithms, and embrace novel technologies to refine and validate predictive models. These findings emphasize immediate clinical applications and underscore the ongoing evolution and broader scope of orofacial anatomy research.

4. Conclusion

In Conclusion, the Naive Bayes and Logistic Regression models exhibited excellent performance in predicting and classifying upper frenum. The Naive Bayes model demonstrated strong discriminatory ability and overall accuracy. In contrast, the Logistic Regression model achieved perfect scores across all metrics, emphasizing its outstanding predictive accuracy and precision in upper frenum classification. These findings contribute valuable insights into the potential applications of machine learning models in enhancing diagnostic capabilities in dental radiography. Regression analysis identified a significant predictors of high frenal attachment in the upper lip.

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