Machine Learning Prediction of Attrition and Cervical Abrasion Using Clinical Images

Sheefaa [1], M. Jeevitha [2], Pradeep Kumar Yadalam [3*], Soundharya Manogaran [4], Swarnambiga Ayyachamy [5]

[1]Saveetha Dental College and Hospitals, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Chennai, Tamil Nadu, India. Email: isheefaa@gmail.com
[2]Department of Periodontics, Saveetha Dental College and Hospitals, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Chennai, Tamil Nadu, India. Email: jeevitham.sdc@saveetha.com
[3]Department of Periodontics, Saveetha Dental College and Hospitals, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Chennai, Tamil Nadu, India. Email: pradeepkumar.sdc@saveetha.com
[4]Department of oral biology, Saveetha Dental College and Hospitals, Saveetha Institute of Medical and Technical Sciences (SIMATS), Saveetha University, Chennai, Tamil Nadu, India. Email: 152432001.sdc@saveetha.com
[5]Bioinformatics Lab, Department of Biomedical Engineering, Saveetha Engineering, Chennai, Tamil Nadu, India. Email: aswarnambiga@gmail.com
**Corresponding Author: Pradeep Kumar Yadalam*

KEYWORDS
Bioinformatics, Biomedical Engineering, Computational Methodologies, Machine Learning, Personalized Medicine, Systems Biology, Clinical Diagnostics, Predictive Analytics, Genomic and Proteomic Data, Translational Research

ABSTRACT
Bioinformatics serves as a bridge between computational methodologies and the intricate challenges of modern healthcare. At the Bioinformatics Lab, Department of Biomedical Engineering, Saveetha Engineering, India, our research led by Swarnambiga Ayyachamy focuses on developing robust data-driven solutions that address critical needs in clinical diagnostics, personalized medicine, and biomedical innovation. By harnessing advanced machine learning algorithms, statistical modeling, and systems biology approaches, we aim to uncover meaningful patterns in genomic, proteomic, and imaging datasets. Our interdisciplinary efforts strive to optimize patient care by informing precise diagnostics, enhancing therapeutic strategies, and enabling predictive analytics in healthcare. Through collaborative projects with clinicians and researchers, the lab emphasizes translational impact—ensuring that computational discoveries are swiftly integrated into real-world clinical applications.

1. Introduction

A universal problem that occurs predominantly is tooth surface loss. These tooth surface loss can be physiological, mechanical, or chemical-related. Various qualitative and quantitative methods are used to identify the percentage of tooth surface loss. Major tooth surface loss includes attrition and abrasion.[1] Attrition is pathological tooth to tooth wear of dentition caused by bruxism, grinding, or chewing. Abrasion is pathological tooth wear caused by foreign substances commonly seen as a result of tooth brushing. Surface loss gradually increases with age [2], [3].

Tooth wear is a major dental concern, involving two main types: attrition and abrasion. Attrition occurs when teeth grind against each other, primarily due to bruxism, an involuntary habit. This can lead to significant loss of enamel and dentin, resulting in a flattened wear pattern on the occlusal surfaces. This can cause increased tooth sensitivity, changes in occlusion, and even temporomandibular joint (TMJ) disorders [4]. Psychological or physical factors can cause bruxism. Over time, attrition can lead to severe dental issues, including exposure to underlying dentin, causing pain and increased susceptibility to decay. Regular dental check-ups are crucial for early identification and management of attrition, with mouthguards often used to protect teeth from further wear [5].

Abrasion is a form of dental wear caused by external friction, often caused by improper brushing techniques or abrasive toothpaste. It can lead to increased tooth sensitivity and an aesthetic decline in appearance, making teeth more vulnerable to thermal stimuli and decay. Preventive measures include educating patients on proper brushing techniques, using soft-bristled toothbrushes, and avoiding abrasive toothpaste. [6], [7] The rise in digital technology has sparked a growing interest in using artificial intelligence or machine learning in dentistry for diagnosis, decision-making, treatment planning, and treatment prediction. This technology can quickly and accurately diagnose problems, allowing clinicians to plan appropriate treatments and reducing the risk of diagnostic errors. Machine learning is crucial in predicting attrition and cervical abrasion in clinical images, particularly in the medical and dental fields. Early detection of these conditions is essential for effective treatment, preventing severe dental problems, and improving patient outcomes. Predictive models can assist healthcare providers in offering personalized treatment plans, improving overall care and satisfaction. Resource optimization is another benefit of using machine learning to predict dental issues. Care is directed where needed by allocating time and attention to patients at higher risk. Early detection and preventive care can significantly reduce costs associated with advanced treatments. Data-driven decisions are made using machine learning, utilizing vast amounts of clinical image data to produce meaningful insights. Automating the prediction process can help in settings lacking specialists, allowing for wider access to predictive care.

Machine learning in prediction involves data collection, preprocessing, feature extraction, model selection, training, evaluation, deployment, and continuous learning[8]. The final model can be integrated into healthcare settings, helping practitioners diagnose and make treatment recommendations based on image inputs. In conclusion, machine learning in predicting attrition and cervical abrasion is important in enhancing patient care, improving early detection, and optimizing healthcare resources. The integration of machine learning in this domain allows for innovative solutions that bridge gaps in traditional diagnostic methods, pushing the boundaries of dental health management toward more proactive and effective strategies[9].

SqueezeNet is a specific convolutional neural network (CNN) architecture designed with certain advantages for image classification tasks. SqueezeNet is a compact machine learning model that stands out from traditional models and neural network architectures due to its small size, efficient inference, transfer learning, and competitive accuracy on standard image classification benchmarks. It uses a "fire modules" strategy to reduce dimensionality and expand the number of parameters, ensuring the expressive power needed for complex image classification tasks. SqueezeNet's compact design allows it to perform faster inference on devices with limited computation resources, making it suitable for real-time applications. Transfer learning allows SqueezeNet to be fine-tuned for specific tasks, allowing it to easily adapt to new image classification tasks with a smaller dataset. Its architecture also provides regularization effects, helping mitigate overfitting for smaller datasets. SqueezeNet's flexibility and scalability make it easy to extend or modify[10], [11].

Compared to traditional machine learning models, SqueezeNet outperforms traditional methods in feature learning, handling complexity, scalability, and end-to-end learning. It automatically learns hierarchical features from raw pixel data, handles complex transformations or patterns, and supports end-to-end training, optimizing the entire pipeline from raw image input to classification output. In conclusion, SqueezeNet stands out in the image classification landscape due to its small size, efficiency, and ability to learn complex patterns from raw image data without extensive manual feature engineering. It offers a powerful alternative to traditional machine learning models and larger deep learning architectures. It is especially valuable when computational resources are limited or rapid inference is essential. The aim of our study is to explore and analyze the diagnosis of attrition and abrasion by using squeeze net algorithms.

2. Materials and Methods

The ethical committee of Saveetha Dental College and Hospitals approved the study. The intra-oral photographs of attrition and abrasion were obtained from DIAS. A total of 100 photographs, out of which 50 were attrition-based and 50 were abrasion-based with expert manual labeling. After retrieving and expert labeling, annotation and segmentation were done and subjected to 80 percent training and 20 percent testing for analysis.

Squeezenet Architecture:

SqueezeNet is a highly efficient deep-learning architecture designed for image classification tasks. It is characterized by its small model size while maintaining competitive accuracy compared to larger models. SqueezeNet is a convolutional neural network that uses Fire Modules to squeeze and expand layers to reduce dimensionality and representation capacity. It has reduced parameters, making it suitable for mobile and embedded applications. The architecture also includes pooling layers to maintain spatial hierarchies and reduce computational load. Global Average Pooling replaces fully connected layers in traditional networks, reducing model size and avoiding overfitting. Embeddings are used in healthcare and dental applications to represent patient characteristics, clinical signs, and other features for diagnosis and predictive analytics.

SqueezeNet architecture combined with embeddings can be used to analyze tooth wear. The process involves gathering a dataset of images of dental conditions associated with attrition and abrasion, along with patient data. The images are processed to train the SqueezeNet model, while the patient data is transformed into embeddings. SqueezeNet extracts features from dental images and learning patterns indicative of tooth wear. Embeddings are created for categorical variables and features related to tooth wear, such as bruxism severity, oral hygiene practices, and diet. The output features from the SqueezeNet and the generated embeddings are combined, resulting in a robust predictive model. The integrated model can be used to classify tooth wear types or predict the risk of progression of attrition and abrasion. This hybrid approach can enhance diagnostic processes and tailor interventions based on individual risks and conditions, ultimately improving patient outcomes in dental health.

A. Random Forest Architecture

Random Forest is an ensemble learning method commonly used for classification and regression tasks. Random Forest is a machine-learning model that uses multiple decision trees to construct models during training time. The architecture consists of an ensemble of decision trees, each constructed independently from a bootstrap sample. Bagging reduces variance and prevents overfitting, while feature randomness adds an additional layer of randomness. Each tree is built by recursively splitting data based on the feature that leads to the best separation, using metrics like Gini impurity or entropy for classification tasks and mean squared error (MSE) for regression tasks.

Predictions are made using the ensemble, with the final prediction determined by majority voting for classification tasks and averaged for regression tasks. Random Forest provides insights into the importance of each feature in making predictions and identifying which features are most influential. Out-of-bag (OOB) error estimation estimates the model's performance, measuring how well the model generalizes. This method excels in accuracy, resilience to overfitting, and ease of use, making it a popular choice in many machine learning applications.

B. Logistics Regression Architecture

Logistic Regression is a probabilistic framework for binary classification problems where the outcome variable takes on two possible values. It involves a linear combination of input features, represented mathematically as $z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 +... + \beta_n x_n$. The output of this linear combination is transformed using the sigmoid function, which squashes the output to a range between 0 and 1. This transformation allows the model to predict probabilities indicating the likelihood of the positive class.

The sigmoid function gives the predicted probability that an instance belongs to the positive class. The model uses a threshold to convert predicted probabilities into class labels, creating a decision boundary at the threshold. The cost function is trained using maximum likelihood estimation, often using binary cross-entropy (or log loss) to measure the difference between predicted probabilities and actual labels.

Optimization techniques, such as gradient descent, are employed to find the optimal weights that minimize the cost function.

Logistic Regression can be extended to multinomial logistic Regression for multiclass classification problems, using multiple binary classifiers or a generalization of the logistic function. Its interpretability is one of its advantages, as the coefficients associated with each feature can be interpreted as the change in the log odds of the outcome for a one-unit increase in the feature.

3. Results

The Random Forest model had a good discriminative ability, with an AUC of 0.872, indicating perfect discrimination. Logistic Regression, on the other hand, showed slightly better performance, suggesting it might be marginally more effective at distinguishing between the presence and absence of conditions. The CA (Classification Accuracy) measured the proportion of true results among the cases examined. The Logistic Regression model outperformed Random Forest regarding overall accuracy by about 3.2%, indicating it correctly predicted a higher proportion of cases. The F1 score, the harmonic mean of precision and recall, was higher in Logistic Regression than in Random Forest, suggesting it is better at balancing the two. The Logistic Regression model also had a higher precision, indicating fewer false positives than Random Forest. In conclusion, the Logistic Regression model outperforms the Random Forest model in predicting attrition and cervical abrasion using clinical images, achieving better accuracy, F1 score, precision, and recall.

Table 1 Evaluates the performance of two predictive models, Random Forest, and Logistic Regression, in predicting attrition and cervical abrasion using clinical images.

Model	AUC	CA	F1	Precision	Recall
Random Forest	0.872	0.684	0.664	0.663	0.684
Logistic Regression	0.875	0.716	0.721	0.730	0.716

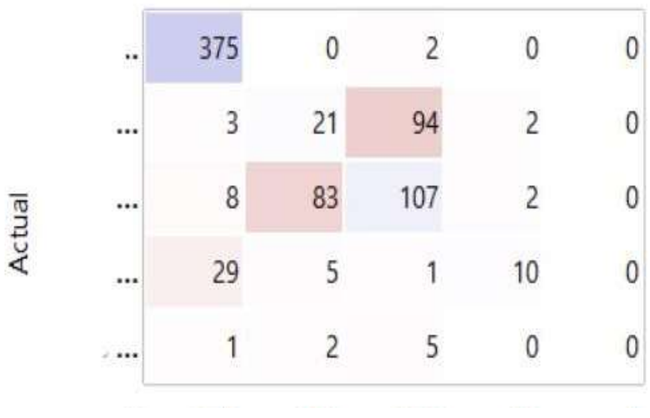

Fig. 1. Shows the confusion matrix of random forest with predicted versus actual across attrition and abrasion.

Overall, the model achieves its highest accuracy with **Class A**, which shows minimal misclassification (375 correct vs. 2 incorrect). This indicates the model has strong predictive power for the features that characterize Class A. However, there is substantial confusion between **Class B and Class C**: while Class B logs only 21 correct predictions and a large number misclassified as C, Class C is similarly misclassified into B, indicating a mutual overlap in their feature sets.

Class D demonstrates moderate accuracy, with 10 correct predictions but a notable number misclassified as A, implying potential data imbalance or insufficient differentiation in features between these two classes. **Class E** is the least recognized, with no correct predictions; instances are scattered among Classes A, B, and C, pointing to the likelihood of too few data samples for E or a lack of distinct features that would separate it from other classes. In summary, although the model is quite effective for Class A, it needs improvement in distinguishing B from C, reducing overlap between D and A, and properly learning the characteristics of Class E.

Actual	...	376	0	1	0	0
	...	0	36	84	0	0
	...	5	94	93	0	8
	...	0	12	1	32	0
	...	0	1	7	0	0

Fig.2. Shows the confusion matrix of Logistic Regression with predicted versus actual across attrition and abrasion.

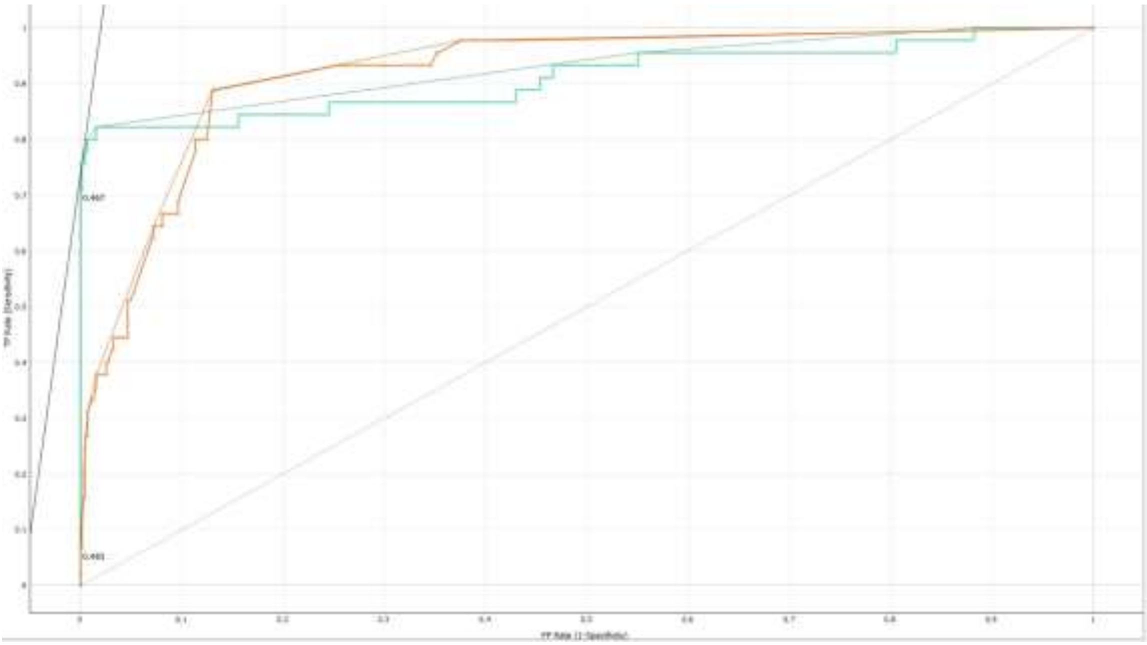

Fig. .3. Shows the ROC curve of attrition and abrasion, with logistics regression showing better accuracy.

Fig.4. Cervical abrasion using clinical images

4. Discussion

Evaluated a deep learning method for diagnosis in various dentistry departments, such as endodontics, periodontics, and orthodontics. The algorithm's specificity and accuracy of diagnosis were 81.8% and 83.3%, respectively, equivalent to clinical professionals' 81.1% and 83.2% values. According to the author, deep learning models have ensured that AI is used in dentistry safely and controlled, ensuring that humans can oversee treatment and make knowledgeable decisions [11], [12]. Similarly, used AI for caries detection, Because of their significantly higher sensitivity (0.81; 0.74-0.87 compared with 0.72; 0.64-0.79; p0.05) and unaffected specificity ($p>0.05$), AI demonstrated a significantly higher mean (95% CI) area under the Receiver-Operating-Characteristics curve than those without AI (0.85; 0.83-0.86; p0.05).AI can improve dentists' diagnostic precision, mostly by sharpening their senses for spotting enamel abnormalities, but it may also lead to more invasive treatment choices.

The current study showed that the AI model demonstrated high accuracy and reliability in detecting and identifying attrition and abrasion. The Random Forest model demonstrated perfect discrimination, but Logistic Regression performed slightly better in distinguishing between conditions. It outperformed Random Forest by 3.2% in overall accuracy, indicating a higher proportion of cases correctly predicted. Logistic Regression also had a higher F1 score, indicating a balance between precision and recall. It also had higher precision, indicating fewer false positives. In conclusion, Logistic Regression outperforms Random Forest in predicting attrition and cervical abrasion using clinical images, achieving better accuracy, F1 score, precision, and recall. (fig-2,3,4) (Table 1).

Future directions for predictive model optimization include using advanced algorithms like gradient boosting or neural networks, incorporating additional features like demographic and longitudinal clinical data, using k-fold cross-validation techniques, real-world validation in clinical settings, and integrating interpretability tools like SHAP values [13], [14], [15]. However, limitations include data quality, overfitting risk, limited complexity, interpretability issues, and the need for dynamic approaches for evolving patient profiles. These limitations may affect model performance and require further exploration and development to improve predictive accuracy.

Meanwhile, according to our experiments, the model can also localize the two types of findings: attrition and abrasion on clinical photos. The AUC of our research was 87% in both attrition and abrasion [15], [16], [17]. Overall, the present study shows the potential of deep learning for enabling the screening of dental diseases among large populations. With the help of intraoral clinical pictures that may be taken with smartphones and other widely accessible devices, deep learning promises to enable the cost-effective screening of dental problems across broad populations. This study's findings align with those of prior investigations that have shown neural networks' capacity to detect and classify dental cavities in a manner comparable to that of skilled dentists. The findings of this study have significant implications for clinical practice. Machine learning algorithms can be useful in improving the accuracy and efficiency of detection and classification of dental caries. Automated detection and classification can assist clinicians in the early diagnosis of dental caries, thereby enabling preventive measures to be implemented [18-20].

5. Conclusion

The analysis of Logistic Regression and Random Forest algorithms for predicting dental outcomes shows promising accuracy. However, limitations like data quality issues and overfitting may affect performance. Future directions should focus on advanced optimization strategies, robust cross-validation methods, and integrating additional features. Model explainability is crucial for clinicians to trust predictions. Validating these models in real-world clinical environments is essential to determine their effectiveness and reliability in improving patient care in dentistry.

References:

[1] R. P. Shellis and M. Addy, "The interactions between attrition, abrasion and erosion in tooth wear.," *Monogr Oral Sci*, vol. 25, pp. 32–45, 2014, doi: 10.1159/000359936.

[2] D. Bartlett and S. O'Toole, "Tooth wear and aging.," *Aust Dent J*, vol. 64 Suppl 1, pp. S59–S62, Jun. 2019, doi: 10.1111/adj.12681.

[3] P. Wetselaar and F. Lobbezoo, "The tooth wear evaluation system: a modular clinical guideline for the diagnosis and management planning of worn dentitions.," *J Oral Rehabil*, vol. 43, no. 1, pp. 69–80, Jan. 2016, doi: 10.1111/joor.12340.

[4] R. Wadia, "Tooth wear.," Jan. 2021, *England*. doi: 10.1038/s41415-021-2611-1.

[5] S. Salanitri and W. K. Seow, "Developmental enamel defects in the primary dentition: aetiology and clinical management.," *Aust Dent J*, vol. 58, no. 2, pp. 133–40; quiz 266, Jun. 2013, doi: 10.1111/adj.12039.

[6] D. A. Seligman and A. G. Pullinger, "Dental attrition models predicting temporomandibular joint disease or masticatory muscle pain versus asymptomatic controls.," *J Oral Rehabil*, vol. 33, no. 11, pp. 789–799, Nov. 2006, doi: 10.1111/j.1365-2842.2006.01650.x.

[7] J. S. Rees and S. Somi, "A guide to the clinical management of attrition.," *Br Dent J*, vol. 224, no. 5, pp. 319–323, Mar. 2018, doi: 10.1038/sj.bdj.2018.169.

[8] M. Fukuda *et al.*, "Evaluation of an artificial intelligence system for detecting vertical root fracture on panoramic radiography.," *Oral Radiol*, vol. 36, no. 4, pp. 337–343, Oct. 2020, doi: 10.1007/s11282-019-00409-x.

[9] A. Haidan, O. Abu-Hammad, and N. Dar-Odeh, "Predicting Tooth Surface Loss Using Genetic Algorithms-Optimized Artificial Neural Networks," *Comput Math Methods Med*, vol. 2014, 2014, doi: 10.1155/2014/106236.

[10] M. Murata *et al.*, "Deep-learning classification using convolutional neural network for evaluation of maxillary sinusitis on panoramic radiography.," *Oral Radiol*, vol. 35, no. 3, pp. 301–307, Sep. 2019, doi: 10.1007/s11282-018-0363-7.

[11] L. Jiang, D. Chen, Z. Cao, F. Wu, H. Zhu, and F. Zhu, "A two-stage deep learning architecture for radiographic staging of periodontal bone loss.," *BMC Oral Health*, vol. 22, no. 1, p. 106, Apr. 2022, doi: 10.1186/s12903-022-02119-z.

[12] R. Kuwana *et al.*, "Performance of deep learning object detection technology in the detection and diagnosis of maxillary sinus lesions on panoramic radiographs.," *Dentomaxillofac Radiol*, vol. 50, no. 1, p. 20200171, Jan. 2021, doi: 10.1259/dmfr.20200171.

[13] K. L. Devito, F. de Souza Barbosa, and W. N. Felippe Filho, "An artificial multilayer perceptron neural network for diagnosis of proximal dental caries.," *Oral Surg Oral Med Oral Pathol Oral Radiol Endod*, vol. 106, no. 6, pp. 879–884, Dec. 2008, doi: 10.1016/j.tripleo.2008.03.002.

[14] H.-J. Chang *et al.*, "Deep Learning Hybrid Method to Automatically Diagnose Periodontal Bone Loss and Stage Periodontitis.," *Sci Rep*, vol. 10, no. 1, p. 7531, May 2020, doi: 10.1038/s41598-020-64509-z.

[15] M. T. Alkurt, I. Peker, O. Bala, and B. Altunkaynak, "In vitro comparison of four different dental X-ray films and direct digital radiography for proximal caries detection.," *Oper Dent*, vol. 32, no. 5, pp. 504–509, 2007, doi: 10.2341/06-148.

[16] F. De Felice *et al.*, "Prediction of Recurrence by Machine Learning in Salivary Gland Cancer Patients After Adjuvant (Chemo)Radiotherapy.," *In Vivo*, vol. 35, no. 6, pp. 3355–3360, 2021, doi: 10.21873/invivo.12633.

[17] I. Peker, M. Toraman Alkurt, and B. Altunkaynak, "Film tomography compared with film and digital bitewing radiography for proximal caries detection.," *Dentomaxillofac Radiol*, vol. 36, no. 8, pp. 495–499, Dec. 2007, doi: 10.1259/dmfr/13319800.

[18] Ali AS, Varghese SS, Shenoy RP. Cervical abrasion, sexual dimorphism, and anthropometric tooth dimension. Journal of Pharmacy and Bioallied Sciences. 2022 Jul 1;14(Suppl 1):S378-83.

[19] Ali AS, Varghese SS, Shenoy RP. Association between cervical abrasion, oral hygiene practices and buccolingual dimension of tooth surfaces: a cross-sectional study. Journal of Pharmacy and Bioallied Sciences. 2022 Jul 1;14 (Suppl 1):S403-9.

[20] Ali AS, Varghese SS, Shenoy RP. The design, development, and calibration of cervical abrasion index of treatment needs probe for measurement of cervical abrasion. Journal of Pharmacy and Bioallied Sciences. 2022 Jul 1;14(Suppl 1): S384-9.