Deep Learning-Powered Dental Diagnostics: Tooth Localization and Condition Assessment from Bitewing X-Rays

G Jayakumar [1], K Yatheendra[2], G Swapna[3], G Viswanath[4]

[1] P.G Scholar, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: gedijayakumar14@gmail.com , ORCID-ID: 0009-0002-9130-0748

[2] Assistant Professor, Department of AI &ML, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: k.yatheendra84@gmail.com , ORCID-ID: 0009-0003-1382-8587

[3] Assistant Professor, Apollo institute of pharmaceutical sciences, The Apollo University, Chittoor, India. E-mail: swapnagv111@gmail.com , ORCID-ID: 0000-0002-9340-4148

[4] Associate Professor, Dept. of AI & ML, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: viswag111@gmail.com , ORCID-ID: 0009-0001-7822-4739

Area/Section: Engineering with Medical Background
Type of the Paper: Regular Paper
Type of Review: Peer Reviewed as per |C|O|P|E| guidance.
Indexed in: OpenAIRE.
DOI: https://doi.org/10.5281/zenodo.15479281
Google Scholar Citation: IJHSP

How to Cite this Paper:

Jayakumar, G., Yatheendra, K., Swapna, G. & Viswanath, G.(2025). Deep Learning-Powered Dental Diagnostics: Tooth Localization and Condition Assessment from Bitewing X-Rays. *International Journal of Health Sciences and Pharmacy (IJHSP)*, *9*(1), 105-114. DOI: https://doi.org/10.5281/zenodo.15479281

International Journal of Health Sciences and Pharmacy (IJHSP)
A Refereed International Journal of Srinivas University, India.

Crossref DOI: https://doi.org/10.47992/IJHSP.2581.6411.0135

Received on: 16/04/2025
Published on: 21/05/2025

Deep Learning-Powered Dental Diagnostics: Tooth Localization and Condition Assessment from Bitewing X-Rays

G Jayakumar [1], K Yatheendra[2], G Swapna[3], G Viswanath[4]

[1] P.G Scholar, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: gedijayakumar14@gmail.com , ORCID-ID: 0009-0002-9130-0748

[2] Assistant Professor, Department of AI &ML, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: k.yatheendra84@gmail.com , ORCID-ID: 0009-0003-1382-8587

[3] Assistant Professor, Apollo institute of pharmaceutical sciences, The Apollo University, Chittoor, India. E-mail: swapnagv111@gmail.com , ORCID-ID: 0000-0002-9340-4148

[4] Associate Professor, Dept. of AI & ML, Sri Venkatesa Perumal College of Engineering & Technology, Puttur, Email: viswag111@gmail.com , ORCID-ID: 0009-0001-7822-4739

ABSTRACT

Periodontitis is a prevalent dental disease marked by bacterial infection of the alveolar bone surrounding the tooth; early identification and precise intervention are essential to avert severe outcomes, together with tooth loss. Historically, the prognosis of periodontal ailment relies upon at the guide identification and category through dental specialists, requiring substantial skill and often proving to be time-consuming. This study examines the application of sophisticated neural network architectures to automate the detection and categorization of periodontitis using dental imaging datasets. Convolutional Neural Networks (CNNs) were applied to assess dental pictures, permitting early illness detection and decreasing dependence on guide evaluations. A comparative investigation of several optimization strategies in neural networks become accomplished to assess their effect on detection performance. The findings reveal that the proposed method attained a detection accuracy of 96.93%, illustrating the capability of automated structures to improve diagnostic precision, efficiency, and scalability in periodontitis detection. This method could markedly beautify patient effects while optimizing healthcare workflows.

Keywords: Periodontitis, Early Detection, Convolutional Neural Networks, Deep Learning, Dental Imaging, Disease Classification, Automated Systems, Diagnostic Accuracy, Optimization Strategies, Clinical Workflows.

1. INTRODUCTION:

Oral diseases rank among the most prevalent health disorders worldwide, with the "world health organization (WHO)" indicating that more than 3.5 a billion individuals around the world are affected by oral diseases [1]. Tooth decay worldwide impact on about 2 billion individuals and serious periodontal diseases that affect about 1 billion people (around 30% of the global populace), are among the most common oral health concerns nowadays [1][7]. Periodontal sickness, a severe dental suffering typically induced by bacterial infections within the periodontal tissues, is predominantly exacerbated by means of inadequate oral hygiene and tobacco use. [5][6]. normal manifestations of periodontal disease embody hemorrhaging gums, gingivitis, halitosis, dental sensitivity, and gum recession, with superior times potentially resulting in enamel loss. [6]. the diagnosis of periodontal disease commences with a visible exam of the gums to come across any signs of redness or irritation.

The periodontal probe is used to measure the periodontal pocket intensity and evaluate the degree of damage. X -ray imaging is applied to assess the OSS structure around enamel, detecting the irregularity of the tooth alignment and verifying the Gingiva recession times. Nevertheless, the conventional method of detecting periodontal disease is labor-intensive and predominantly depends on physical assessment [14][5].

2. OBJECTIVES:

(1) To automate the diagnosis of periodontitis by leveraging deep learning techniques on dental imaging datasets. This reduces reliance on manual assessment by dental professionals and speeds up the diagnostic process. The approach aims to facilitate early disease detection and timely intervention through AI-driven tools.
(2) To implement and evaluate "Convolutional Neural Networks (CNNs)" for the accurate detection of periodontal disease. CNN models are trained to analyze visual patterns in dental images for precise classification of infection severity. The objective is to enhance the reliability and consistency of diagnoses across varied patient cases.
(3) To assess the effectiveness of different neural network optimization strategies in improving detection performance. A comparative study is carried out to determine the best-performing optimization method for the CNN models. This helps in fine-tuning the system to achieve the highest possible diagnostic accuracy and efficiency.
(4) To demonstrate the clinical potential of automated periodontitis detection systems in real-world dental workflows. The model achieved 96.93% accuracy, showing strong applicability in enhancing healthcare delivery. This objective supports the integration of AI for better patient outcomes and streamlined dental care services.

3. REVIEW OF LITERATURE/ RELATED WORKS:

Recent years have witnessed substantial progress in the usage of "artificial intelligence (AI) and deep learning" methodologies for the identification and diagnosis of dental ailments, particularly periodontal disease. numerous studies have concentrated on automating the identification of dental problems through diverse imaging modalities, including X-rays and intraoral pictures, to diminish dependence on manual assessments and enhance diagnostic precision.

Deep learning methodologies, especially "Convolutional Neural Networks (CNNs)", have been effectively hired to detect dental caries and periodontal lesions with notable effectiveness. Li et al. (2021) illustrated the efficacy of CNNs in identifying apical lesions in periapical radiographs, with full-size detection accuracy [5]. A study through Bui et al. (2022) applied the YOLOv3 model for tooth localization in panoramic radiographs, enhancing the diagnostic procedure for dental diseases, such as periodontal disease [1]. Extra research by Chen et al. (2021) validated that CNNs might enhance the accuracy of peri-implantitis detection in periapical radiographs, in addition underscoring the promise of deep mastering in diagnosing periodontal diseases [3].

Furthermore, automatic techniques were created to identify white spot lesions and other initial indicators of dental caries via cell photography. Ding et al. (2021) utilized YOLOv3 to identify dental cavities in phone photos, illustrating the viability of the usage of AI into cellular health applications for dental diagnostics [30]. numerous research have tested the application of AI models for the detection and classification of dental problems in bitewing and panoramic radiographs, demonstrating the capacity of deep learning to improve diagnostic techniques [26][18].

Furthermore, the domain has exhibited encouraging outcomes in making use of AI for the automated identification and enumeration of teeth in dental radiographs, a vital factor inside the diagnosis and treatment making plans of periodontal disease. Yasa et al. (2020) introduced an AI-driven methodology for the automatic detection and numbering of teeth in bite-wing radiographs, demonstrating that deep learning can also substantially decrease the time and knowledge needed for manual annotation [7].

These trends illustrate the increasing potential of AI and deep learning in improving the speed, precision, and efficacy of periodontal ailment diagnosis. Notwithstanding those achievements, in addition take a look at is critical to augment the resilience and scalability of these computerized structures in various clinical environments, hence enhancing patient consequences and clinical processes.

Table 1: Comparison Table for Related Work

Sl.No	Area & Focus of the Research	The result of the Research	Reference
1	Tooth localization using YOLOv3 for dental diagnosis on panoramic radiographs.	Achieved high accuracy in automatically locating teeth, improving diagnostic efficiency for dental professionals.	T. H. Bui et al., (2022) [1]
2	CNN-based system for measuring peri-implantitis damage on periapical film.	Demonstrated precise detection and measurement of implant damage, enhancing clinical implant outcome evaluation.	Y.-C. Chen et al., (2023) [3]
3	Detection of dental apical lesions using CNNs on periapical radiograph.	CNN model accurately identified apical lesions, showing potential for aiding early diagnosis in dental imaging.	C.-W. Li et al., (2021) [5]
4	Automatic teeth detection and numbering in dental bite-wing radiographs.	Developed an AI model for automatic tooth detection and numbering, simplifying digital dental workflows.	Y. Yasa et al., (2020) [7]
5	Detecting white spot lesions using deep learning on dental photography.	Deep learning model effectively identified early-stage caries, supporting preventive dental care strategies.	H. Askar et al., (2021) [9]

4. MATERIALS AND METHODS:

The proposed approach seeks to automate the diagnosis and categorization of periodontitis via the utilization of dental imaging datasets and modern deep learning methodologies. A "Neural network (NN)" architecture is established, including each the ADAM and ADAMAX optimization algorithms to assess their influence on model performance. those optimizers are chosen for his or her capability to effectively manage tricky, high-dimensional data and adjust learning prices to beautify convergence, as evidenced in prior research [5][6]. A 2d "Convolutional Neural network (CNN2D)" is applied to extract and examine complicated data from dental snap shots, facilitating correct identification of periodontal ailment. "Convolutional Neural Networks (CNNs)" have tested efficacy in diverse dental imaging applications, such as the identification of apical lesions and caries, through proficiently interpreting radiographs and delivering precise outcomes [1][5]. The system aims to diminish dependence on manual diagnosis by dental practitioners, presenting an green, scalable, and consistent answer for early detection, according with recent improvements in AI-driven dental diagnostic tools [6][7][18]. The proposed approach aims to enhance diagnostic accuracy, optimize the detection procedure, and establish a solid foundation for precise treatment of periodontitis by integrating various methodologies, akin to other effective AI applications in dentistry [14][19].

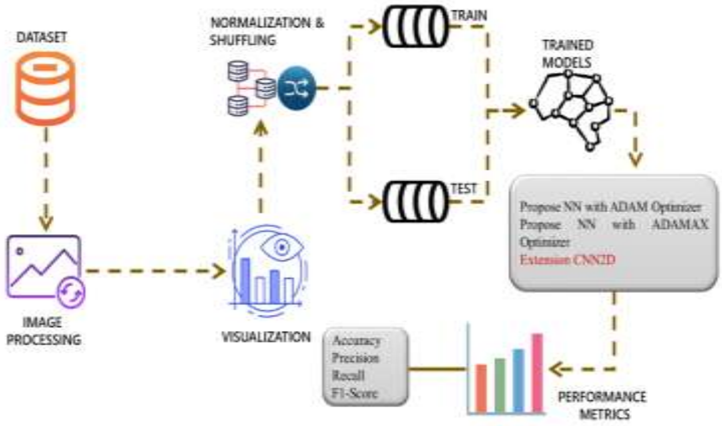


Fig 1: Proposed Architecture

The system architecture (fig. 1) illustrates a "machine learning" pipeline for image classification. The procedure commences with the dataset, which undergoes image preprocessing. The facts is subsequently normalized and randomized for training purposes. The training data is utilized to train neural networks, inclusive of models optimized with Adam and Adamax optimizers, with a probable extension for 2d "CNNs (Convolutional Neural Networks)". Eventually, the models undergo testing. Visualization procedures are utilized to give performance indicators, including "accuracy, precision, recall, and F1-score", for assessing the efficacy of educated models. The workflow encompasses data processing, model training, and performance evaluation.

4.1 Dataset Collection:

The dataset utilized for the proposed method comprises classified dental imaging data specifically intended for the identification and type of periodontitis. The collection encompasses a varied array of dental X-rays and panoramic radiographs, featuring images that depict a spectrum of periodontal disease, ranging from initial indications such as gingivitis to advanced instances that could result in tooth loss. The photographs are annotated by means of dental experts, offering labels for the presence, severity, and type of periodontal damage, alongside pertinent characteristics such as gum recession and bone loss. The dataset furthermore included photos of healthy controls for comparative evaluation. The pics go through preprocessing for uniformity, involving standardization of resolution, dimensions, and color normalization, so facilitating a success feature extraction by the neural network. The data file is divided into training, authentication and testing of subset to evaluate the generalization skills and performance of the model in many environments. This data file serves as the basis for training and verifying the proposed deep learning model.

4.2 Pre-Processing:

The photos are processed, resized, and accurately labeled for training purposes. Image data is transformed right into a numpy array format for next processing, enabling green control and manipulation of the data in "deep learning" models [6][14]. The processed images and their accompanying labels are eventually saved for training, making sure that every photo is accurately matched with its appropriate label, a conventional procedure in image-based diagnostic systems [5].

4.2.1 Visualization

Visualization strategies are utilized to present example photographs alongside their respective labels, facilitating the examination of the dataset. This stage aids in assessing the quality and variability of the pictures previous to version training, which is crucial for verifying the dataset's appropriateness for the job and detecting any potential preprocessing concerns. [7][10].

4.2.2 Shuffling & Normalization

Normalization is utilized to adjust picture pixel values to a standardized variety, hence expediting version convergence and improving training stability, as evidenced by numerous studies in deep learning for dental image processing [1][19]. Shuffling is hired to randomly reorganize the dataset, improving range inside the training batches and mitigating overfitting by guaranteeing that every mini-batch includes a representative sample of the dataset [5][18].

4.3 Training & Testing:

The model is trained with the preprocessed dataset, wherein the photos are enter into the "Convolutional Neural network (CNN)" structure. The training approach utilizes the "ADAM and ADAMAX" optimization algorithms to decrease the loss function and enhance model accuracy. The data file is divided into training, validation and testing of subset, where the training subset is used to optimize the model, validation subset for large fine -tuning of the hyper parameter and test subgroup for performance assessment. Performance parameters, including accuracy and loss, are monitored to assess the version's capacity to generalize and reliably identify periodontitis in novel data [1][6][14].

4.4 Algorithms:

NN with ADAM Optimizer: The "Neural network (NN)" utilizing the ADAM optimizer is a deep learning method that adaptively modifies learning rates throughout the education manner. This optimizer is extensively utilized in diverse packages, including dental photo class, thanks to its proficiency in managing excessive-dimensional statistics and enhancing convergence pace [5][6]. The ADAM optimizer on this system lowers the loss characteristic, facilitating expedited and more dependable learning for periodontitis diagnosis from dental images. The version's adaptive nature allows optimal weight updates, hence improving both accuracy and standard performance in the categorization of periodontal disease detection [1][7].

NN with ADAMAX Optimizer: The ADAMAX optimizer, an enhancement of the ADAM optimizer, is intended to offer advanced performance with sparse data and larger models [6]. The ADAMAX optimizer is hired in this system to train the neural network using dental pictures, enhancing stability during the training manner. It improves convergence speed and mitigates overfitting, ensuring that the model generalizes efficaciously and reliably identifies periodontitis across various picture datasets. This optimizer enhances learning efficiency, especially whilst managing intricate and diverse dental imaging data [5][14].

Extension CNN2D:The 2d "Convolutional Neural network (CNN2D)" is a model engineered to autonomously extract spatial traits from -dimensional images, rendering it suitable for image type tasks, including the detection of periodontal disease in dental radiographs [1][6]. The CNN2D model utilizes convolutional layers to extract great patterns and hierarchical features from images, enabling the network to parent complicated details vital for specific illness identity. This structure markedly enhances the model's accuracy through assimilating both low-degree and excessive-stage features, hence facilitating rapid and precise categorization of periodontitis from dental images [14][18].

5. RESULTS AND DISCUSSION:

Accuracy: A test’s accuracy is its capacity to appropriately differentiate between healthy instances and patients. To evaluate the correctness of a check, one has to determine the percentage of actual positivity and actual negative in every evaluated scenario. Mathematically, it can be stated as follows:

$$"Accuracy = \frac{\mathrm{TP + TN}}{\mathrm{TP + FP + TN + FN}} \; (1)"$$

Precision: The accuracy takes into account the percentage of correctly categorised cases in those known as positive. Consequently, it is stated as a formula for determining accuracy:

$$"Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} \; (2)"$$

Recall: The reminder is a metric in "machine learning" that evaluates the ability of the model to recognize all relevant times of selected elegance. It is a mile ratio of accurately predicted positive observations to overall real positives and offers information about the model efficacy in identifying occurrences of a particular elegance.

$$"Recall = \frac{\text{TP}}{\text{TP + FN}}(3)"$$

F1-Score: The F1 score is a metric for evaluating the accuracy of the "machine learning" model. It integrates accuracy and do not forget the model metrics. The accuracy metric quantifies the frequency of real predictions generated by the model for the duration of the entire data file.

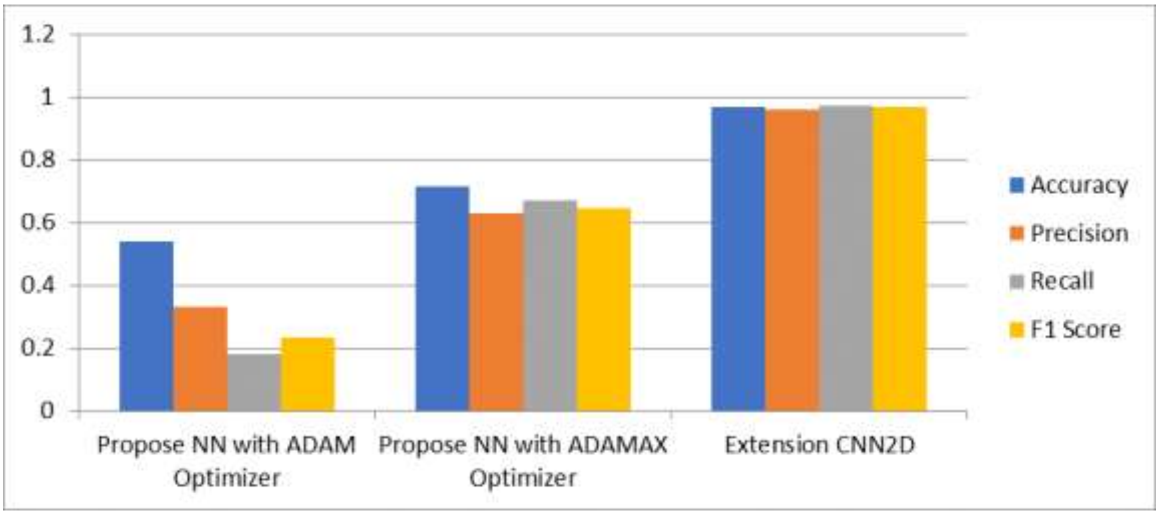
$$"F1\ Score = 2 * \frac{Recall\ X\ Precision}{Recall + Precision} * 100(1)"$$

Table 1 offers the performance metrics—"accuracy, precision, recall, and F1-score"—assessed for each algorithm. The Extension CNN2D attains the greatest scores. Metrics from opportunity algorithms are also provided for comparison.

Table 2: Performance Evaluation Metrics for classification

Model	Accuracy	Precision	Recall	F1 Score
Propose NN with ADAM Optimizer	0.540	0.333	0.180	0.233
Propose NN with ADAMAX Optimizer	0.714	0.630	0.672	0.645
Extension CNN2D	0.969	0.961	0.970	0.966

Fig 2: Comparison Graphs for classification



In Graph 1, accuracy is depicted in light blue, precision in maroon, F1 score in green, and recall in violet. As compared to the other models, the Extension CNN2D has extra performance, attaining the highest values across all metrics. The graphs above visually represent these findings

6. CONCLUSION:

This paper efficaciously tackles the difficulties of automated periodontitis detection with the aid of offering a robust deep learning methodology that employs dental imaging datasets. The system employs advanced neural network topologies to markedly diminish dependence on manual analysis, providing a cheap and scalable answer for the early detection of periodontal disease. Some of the fashions examined, the 2d "Convolutional Neural network (CNN2D)" had the highest accuracy, attaining an astonishing 96.93%, underscoring the model's exceptional potential to extract complex characteristics and provide accurate classifications of periodontal diseases. The suggested technique optimizes the diagnosis process, improving accuracy whilst minimizing the time and knowledge

wished for guide labeling, according with trends in AI-driven dental diagnostics. The results highlight the ability of computerized deep learning frameworks to revolutionize dental diagnostics, mainly in elaborate situations like teeth alignment, hence facilitating enhanced patient outcomes and extra green medical strategies.
Future Scope should strive to improve the specificity of periodontal disease characteristics, facilitating more precise identification and categorization. Mitigating the constraints of conventional CNN models, which includes the vanishing gradient problem, may be accomplished by investigating new designs such as YOLO to beautify computing efficiency and learning proficiency. Furthermore, advanced models like “ResNet and EfficientNet” warrant exploration to beautify accuracy, as they have tested advanced overall performance in analogous situations. The primary goal is to satisfy medical requirements and provide efficient assistance for dental diagnostics, guaranteeing the system's broad applicability in clinical environments.

REFERENCES:

[1] Bui, H. T., Hamamoto, K., & Paing, M. P. (2022). Tooth localization using YOLOv3 for dental diagnosis on panoramic radiographs. *IEEJ Trans. Electron., Inf. Syst.*, 142(5), 557–562.

[2] Viswanath, G. (2022). A Smart Recommendation System for Medicine using Intelligent NLP Techniques. *2022 International Conference on Automation, Computing and Renewable Systems (ICACRS)*, 3(2), 1081-1084.

[3] Jindal, H., Agrawal, S., Khera, R., Jain, R., & Nagrath, P. (2021). Heart disease prediction using machine learning algorithms. *IOP Conf., Mater. Sci. Eng*., 1022(1), 1-11.

[4] Swapna, G., & Bhaskar, K. (2024). Early-Stage Autism Spectrum Disorder Detection Using Machine Learning. *International Journal of HRM and Organizational Behavior*, 12(3), 269-283.

[5] Anitha, S., & Sridevi, N. (2019). Heart Disease Prediction Using Data Mining Techniques . *HAL* ,13(2) ,48-55.

[6] Viswanath, G. (2024). Multiple Cancer Types Classified Using CTMRI Images Based On Learning Without Forgetting Powered Deep Learning Models. *International Journal of HRM and Organizational Behavior*, 12(3), 243-253.

[7] Yasa, Y., Çelik, O., Bayrakdar, I. S., Pekince, A., Orhan, K., Akarsu, S., Atasoy, S., Bilgir, E., Odabas, A., & Aslan, A. F.(2020). An artificial intelligence proposal to automatic teeth detection and numbering in dental bite-wing radiographs. *Acta Odontologica Scandinavica*, 79(4), 275–281.

[8] Viswanath, G., & Swapna, G. (2024). Health Prediction Using Machine Learning with Drive HQ Cloud Security. *Frontiersin Health Informatics*, 13(8), 2755-2761.

[9] Abbas, S., Avelino Sampedro, G., Abisado, M., Almadhor, A. S., Kim, T. H., & Mohamed Zaidi, M. (2023). A novel drug-drug indicator dataset and ensemble stacking model for detection and classification of drug-drug interaction indicators. *IEEE Access*, 11(2), 101525–101536.

[10] Viswanath, G., & Swapna, G. (2025). Data Mining-Driven Multi-Feature Selection for Chronic Disease Forecasting. *Journal of Neonatal Surgery*, 14(5s), 108-124.

[11] Thai, D. T., Minh, Q. T., & Phung, P. H. (2017). Toward an IoT-based expert system for heart disease diagnosis. *in Proc. 28th Mod. Artif. Intell. Cogn. Sci. Conf. (MAICS)*, 1964(1), 157–164.

[12] Viswanath, G. (2024). Personalized Breast Cancer Prognosis through Data Mining Innovations. *Cuestiones de Fisioterapia*, 53(2), 538-548.

[13] Duong, H., Roccuzzo, A., Stähli, A., Salvi, G.E., Lang, N.P., & Sculean, A. (2022). Oral health-related quality of life of patients rehabilitated with fixed and removable implant-supported dental prostheses. *Periodontology* , 88(4), 201–237.

[14] Viswanath, G. (2021). Adaptive Light Weight Encryption Algorithm for Securing Multi-Cloud Storage. *Turkish Journal of Computer and Mathematics Education*, 12(9), 545-554.

[15] Swathy, M., & Saruladha, K. (2022). A comparative study of classification and prediction of cardio-vascular diseases (CVD) using machine learning and deeplearning techniques. *ICT Exp*., 8(1) , 109–116.

[16] Muramatsu, C., Morishita, T., Takahashi, R., Hayashi, T., Nishiyama, W., Ariji, Y., Zhou, X., Hara, T., Katsumata, A., Ariji, E., et al. (2021). Tooth detection and classification on panoramic radiographs for automatic dental chart filing: Improved classification by multi-sized input data. *Oral Radiol*, 37(5), 13–19.

[17] Kohlakala, A., Coetzer, J., Bertels, J., & Vandermeulen, D. (2022). Deep learning-based dental implant recognition using synthetic X-ray images. *Med. Biol. Eng. Comput*. 60(6), 2951–2968.

[18] Chen, S. L., Chen, T. Y. Mao, Y. C., Lin, S. Y., Huang, Y. Y., Chen, C. A., Lin, Y. J., Hsu, Y. M., Li, C. A., Chiang, W. Y., et al. (2022). Automated Detection System Based on Convolution Neural Networks for Retained Root, Endodontic Treated Teeth, and Implant Recognition on Dental Panoramic Images. *IEEE Sens*. *J*, 22(5), 23293–23306.

[19] Lin, S. Y., & Chang, H. Y. (2021). Tooth Numbering and Condition Recognition on Dental Panoramic Radiograph Images Using CNNs. *IEEE Access*, 9(4), 166008–166026.

[20] Widiasri, M., Arifin, A. Z., Suciati, N., Fatichah, C., Astuti, E. R., Indraswari, R., Putra, R. H., & Za'In, C. (2022). Dental-YOLO: Alveolar Bone and Mandibular Canal Detection on Cone Beam Computed Tomography Images for Dental Implant Planning. *IEEE Access* , 10(3), 101483–101494.

[21] Swapna, G. (2023). A Drug-Target Interaction Prediction Based on Supervised Probabilistic Classification. *Journal of Computer Science*, 19(3), 1203-1211.

[22] Padmaja, B., Srinidhi, C., Sindhu, K., Vanaja, K., Deepika, N. M., & Patro, E. K. R. (2021). Early and accurate prediction of heart disease using machine learning model. *Turkish J. Comput. Math. Educ.*, 12(6), 4516–4528.

[23] Viswanath, G. (2024). Machine-Learning-Based Cloud Intrusion Detection. *International Journal of Mechanical Engineering Research and Technology*, 16(5), 38-52.

[24] Singh, P., Pal, G. K., & Gangwar, S. (2022). Prediction of cardiovascular disease using feature selection techniques. *Int. J. Comput. Theory Eng*., 14(3), 97–103.

[25] Swapna, G., & Bhaskar, K. (2024). Malaria Diagnosis Using Double Hidden Layer Extreme Learning Machine Algorithm With Cnn Feature Extraction And Parasite Inflator. *International Journal of Information Technology and Computer Engineering*, 12(4), 536-547.

[26] Karatas, O., Cakir, N. N., Ozsariyildiz, S. S., Kis, H. C., S. Demirbuga, S., & Gurgan, C. A. (2021). A deep learning approach to dental restoration classification from bitewing and periapical radiographs. *Quintessence Int.*, 52(7), 568–574.

[27] Viswanath, G., & Swapna, G. (2025). Diabetes Diagnosis Using Machine Learning with Cloud Security. *Cuestiones de Fisioterapia*, 54(2), 417-431.

[28] Joshi, S., & Abdelfattah, E. (2021). Multi-class text classification using machine learning models for online drug reviews. *in Proc. IEEE World AI IoT Congr. (AIIoT)*, 8(3), 262–267.

[29] Viswanath, G. (2024). Improved Light GBM Model Performance Analysis and Comparison for Coronary Heart Disease Prediction. *International Journal of Information Technology and Computer Engineering*, 12(3), 658-672.

[30] Ohata, E. F., Mattos, C. L. C., Gomes, S. L., Rebouças, E. D. S., & Rego, P. A. L. (2022). A text classification methodology to assist a large technical support system. *IEEE Access*, 10(2), 108413–108421.

[31] Viswanath, G. (2024). Enhancing Cloud Security: A Blockchain-Based Verification Framework for Multi-Cloud Virtual Machine Images. *Frontiers in Health Informatics*, 13(3), 9535-9549.

[32] Estai, M., Tennant, M., Gebauer, D., Brostek, A., Vignarajan, J., Mehdizadeh, M., & Saha, S. (2022). Evaluation of a deep learning system for automatic detection of proximal surface dental caries on bitewing radiographs. *Oral Surg. Oral Med. Oral Pathol. Oral Radiol*. 134(2), 262-270.

[33] Viswanath, G. (2021). Hybrid encryption framework for securing big data storage in multi-cloud environment. *Evolutionary intelligence*, 14(2), 691-698.

[34] Chen, S. L., Chen, T. Y., Huang, Y. C., Chen, C. A., Chou, H. S., Huang, Y. Y., Lin, W. C., Li, T. C., Yuan, J. J., Abu, P. A. R., et al. (2022). Missing Teeth and Restoration Detection Using Dental Panoramic Radiography Based on Transfer Learning with CNNs. *IEEE Access*, 10(2), 118654–118664.

[35] Viswanath, G. (2023). A Real-Time Case Scenario Based On URL Phishing Detection Through Login URLS. *Material science and technology*, 22(9), 103-108.

****