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Enhancing Endodontic Precision: A Novel AI-Powered Hybrid Ensemble Approach for Refining Treatment Strategies

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Abstract: Root canal curvature and calcification present challenges during root canal treatment, increasing the risk of procedural mishaps. These factors can jeopardize the management of intra-radicular infection leading to unfavourable treatment outcomes. The present research introduces an innovative approach that utilizes artificial intelligence (AI) to enhance endodontic treatments. The study focuses on the development of a hybrid ensemble classifier, which combines multiple classification algorithms. By harnessing the strengths of these algorithms, the hybrid ensemble classifier improves the accuracy and robustness of classifying various endodontic challenges. The research also incorporates image segmentation techniques to isolate specific regions of interest, including teeth and roots, for further analysis. The segmentation process involves contrast enhancement, adaptive thresholding, contour detection and root segmentation. Through experimentation, the proposed approach demonstrates notable improvements in precision, recall, F1-score, accuracy and overall performance, ultimately refining endodontic treatments. The findings of this research contribute insights and advancements to treatment planning and decision-making processes in the field of endodontics, providing promising avenues for improving the management of endodontic treatments and achieving better treatment outcomes.

Keywords: *Endodontic treatments, Root canal curvature, Artificial intelligence (AI), Hybrid ensemble classifier*

1. Introduction

Dental caries also known as tooth decay or cavities, remains a prevalent issue affecting a significant portion of the global population [1]. Approximately 36% of individuals worldwide suffer from dental caries in their permanent teeth [2]. This condition arises due to the demineralization of inorganic substances and the degradation of organic substances within dental tissues, primarily caused by a combination of bacteria and dietary factors [3]. Bacterial activity in the mouth, particularly the production of lactic acid from sucrose, leads to the breakdown of the tooth surface, resulting in severe dental disease. Studies have shown that individuals who face social or economic disadvantages, have limited education or literacy or have disabilities, are more susceptible to developing dental caries. Tooth loss caused by oral diseases is associated not only with tooth decay but also with potentially harmful dietary changes.

Over the years, various preservation and restoration procedures have been successfully employed to enhance the treatment of dental caries. However, diagnostic approaches for detecting caries have made limited progress due to the complexity of tooth anatomy and detecting and treating still pose significant challenges. Early-stage disease can be challenging to diagnose, particularly when deep crevices, tightly adjacent inter-dental contacts or secondary lesions are present. Treatment options for dental caries typically include fluoride treatments, tooth fillings, root canal therapy or tooth extraction, with root canal therapy being the most effective and restorative treatment option [4]. Despite the advancements in treatment approaches, improving the diagnostic capabilities for caries detection remains a significant area of focus.

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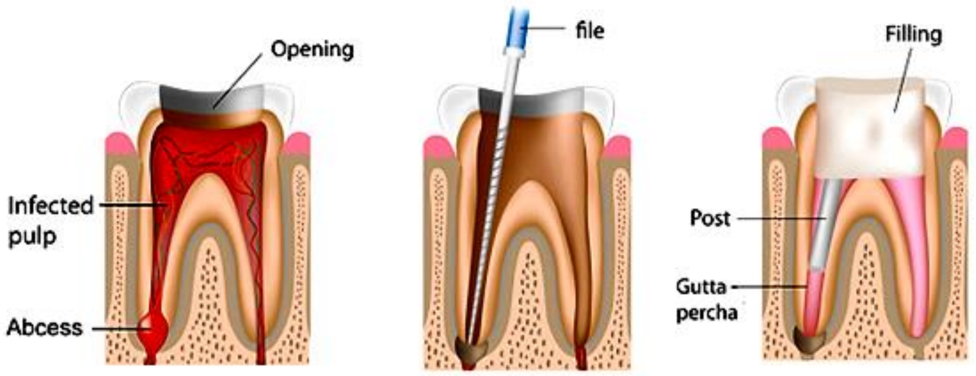
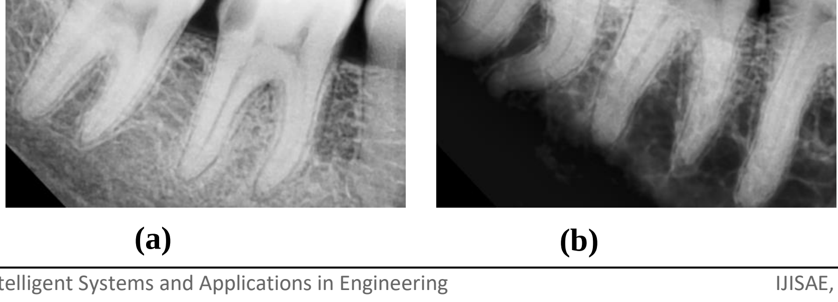


Fig. 1: Root Canal Endodontic Treatment [https://www.se1dentist.com/rooth-canal-treatment]

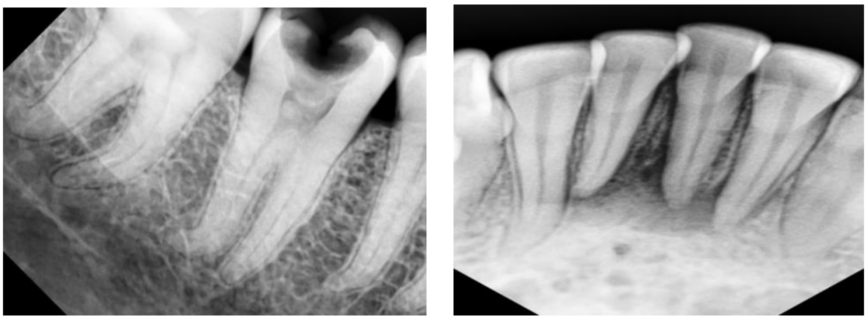
Root canal treatment is a standard dental procedure for addressing caries. Figure 1 shows the overview of Root Canal Endodontic Treatment. Depending on the extent of the decay, the procedure can be completed in one or two/three sittings, with each session lasting approximately 45 minutes. The objective of root canal treatment is to eliminate bacteria from the infected tooth, prevent further bacterial infection and preserve the natural tooth. During the procedure, the infected pulp is removed, and the tooth is thoroughly cleaned, disinfected, filled with a biocompatible material, and sealed. However, the anatomy of teeth can present various complexities that require the expertise of an endodontist. These complexities include narrow canals, long roots, curved canals, multi-curvature, bifurcated canals, abnormal anatomy and calcified roots, which may not be easily discernible from X-ray images. Identifying these complexities is often time consuming and requires the judgment of experienced dentists.

Dental X-ray images face additional challenges, such as quantum, photons, electronic, and quantization noises. These factors can degrade the quality of the dental X-ray images. The images typically consist of areas with high intensity representing teeth, areas with average intensity representing bone, and areas with low intensity representing the background. Uneven exposure can make it difficult to distinguish between tooth and bone areas. Therefore, pre-processing of dental radiographs is essential to enhance the sharpness of dental caries boundaries and increase the contrast between the image background and teeth. In this context, the significance of pre-processing techniques becomes evident, as they play a crucial role in improving the quality and interpretability of dental X-ray images. These techniques aim to enhance the boundaries of dental caries, enabling better identification and differentiation between tooth and bone areas.

Root canal curvature poses a significant challenge in achieving thorough cleaning and shaping of the canal. The curvature limits the accessibility and visibility of the root canal system, making it difficult to remove infected tissue and waste completely. Additionally, calcification can further complicate the procedure by obstructing the root canal space, hindering proper disinfection and shaping. Several procedural problems can arise as a result of these challenges. Narrow or constricted root canals often present difficulties in accessing and treating these effectively. Longer-than-average root structures require specialized techniques and considerations to ensure precise and effective treatment delivery. Asymmetrical dentine removal may cause transportation, where the original canal shape is altered, potentially resulting in a compromised seal and inadequate treatment. Moreover, there is an increased risk of perforation, which can create pathways for bacteria to invade the surrounding tissues. Instrument fracture within the curved trajectories is also a concern, as it can lead to difficulties in retrieval and potentially compromise treatment outcomes. Figure 2. shows the various complexities encountered in tooth anatomy during root canal treatment.



(a) **(b)**



(c) **(d)**

Fig. 2: Complexities in tooth anatomy (a) Calcified Roots, (b) Curved Canal, (c) Narrow Canal, (d) Long root

To address these challenges and improve the endodontic treatments, innovative approaches are being explored. One promising avenue is the integration of artificial intelligence (AI) techniques. AI can aid in refining treatment strategies, enhancing precision, and optimizing decision-making processes. This research aims to introduce a novel approach towards enhancing endodontic treatments using Machine Learning (ML). Specifically, the study focuses on the development of a hybrid ensemble classifier that combines multiple classification algorithms to improve the accuracy and robustness of classifying different endodontic challenges. Additionally, image segmentation techniques are employed to isolate specific regions of interest, such as teeth and roots, for further analysis. These techniques aim to enhance the understanding and management of endodontic treatments, ultimately leading to improved treatment outcomes. By investigating the application of AI and employing advanced classification and segmentation methods, this research aims to provide valuable insights and advancements in the field of endodontics. The findings have the potential to improve treatment planning, decision-making processes and overall effectiveness in managing endodontic treatments.

2. Literature Review

Extensive research has been done to explore the potential of machine learning, deep learning algorithms in various dental applications, such as root morphology assessment, apical lesion detection, teeth detection and numbering, and caries detection [5], [6]. The reviewed studies showcase the application of advanced techniques and methodologies in endodontics, particularly in utilizing AI for diagnosis, treatment planning, and intra-operative guidance. The studies highlight the potential of AI in improving diagnostic accuracy, treatment outcomes, and overall efficiency in endodontic procedures. The findings underscore the importance of continued research and exploration of AI-based approaches to advance endodontics and provide better care to patients.

Karobari et al. [7] have given a comprehensive review of the literature to evaluate the diagnostic and prognostic accuracy of artificial intelligence (AI) in endodontic dentistry. The authors have reviewed a wide range of research articles and studies that utilized AI algorithms for various applications in endodontics.

In their systematic review, Khanagar et al. [8] have explored the developments and performance of AI models specifically designed for application in endodontics. The findings indicate that AI models demonstrate promising results in accurately detecting caries, assessing the complexity of root canals and predicting the success rates of endodontic procedures.

Agrawal and Nikhade [9] have explored the past and present applications of artificial intelligence (AI) in dentistry, including its implications for endodontics. The authors discuss the historical progression of AI in dentistry, starting from early applications to current state-of-the-art developments. The authors further explore the future prospects of AI in dentistry, envisioning advancements such as personalized treatment planning, real-time monitoring, and virtual reality-assisted procedures.

Quaresma et al. [10] have explored the use of cone-beam computed tomography (CBCT) as an intraoperative resource for root canal treatment of severely calcified teeth. The results demonstrate that CBCT provided valuable information during the procedure, aiding in accurate canal identification, negotiation, and filling, ultimately leading to successful root canal treatment.

Setzer et al. [11] have utilized machine learning algorithms and developed a deep learning network to train an AI model for periapical lesion detection. The results demonstrated the effectiveness of the AI model in accurately identifying and classifying periapical lesions in CBCT images, highlighting its potential as a computer-aided diagnostic tool in endodontics.

Pauwels et al [12] have provided a comprehensive introduction to the concepts and applications of AI in dental imaging. The authors highlight the use of machine learning algorithms, deep learning networks and image segmentation techniques in various applications, including caries detection, root canal treatment planning, and image classification.

Aminoshariae et al. [13] have discussed the methodology and techniques employed in AI applications, including machine learning, deep learning, and computer-aided diagnosis systems, highlighting the use of AI in caries detection, root canal treatment planning and decision support systems.

Wen Fu et al [14] address the challenges associated with the restoration of calcified root canals using a novel deep learning approach. The authors report high accuracy rates and low computational times, highlighting the potential of deep learning-based method to improve the efficiency and accuracy of endodontic treatment.

Jae-Hong Lee et al [15] present a comprehensive study on the development of a deep learning-based algorithm for the detection and diagnosis of dental caries. The authors utilize a large dataset of dental images, encompassing various imaging techniques such as digital radiography and intraoral cameras. The findings provide a promising approach to enhance the effectiveness and accuracy of caries diagnosis, leading to improved treatment outcomes and preventive measures.

Laura A. et al [16] present an innovative approach to diagnose dental caries using deep artificial neural networks (ANNs). By leveraging the power of deep learning algorithms, the study aims to improve the accuracy and understanding of caries diagnosis by considering the complex interactions between socioeconomic status, nutritional factors and the presence of caries.

Teruhiko Hiraiwa et al [17] focus on the development of a deep-learning artificial intelligence system for the assessment of root morphology in the mandibular first molar using panoramic radiography. A deep learning algorithm has been developed and trained on a large dataset of panoramic radiographs containing both normal and abnormal root morphologies. The algorithm demonstrates remarkable accuracy in assessing root morphology, outperforming traditional manual methods.

Thomas Ekert et al [18] explore the application of deep learning for the radiographic detection of apical lesions by developing and training a model on a dataset of radiographic images with known apical lesions. The model has demonstrated high accuracy in detecting and localizing apical lesions, providing an efficient and objective approach for their diagnosis.

Hu Chen et al [19] introduce a deep learning approach for automatic teeth detection and numbering based on object detection in dental periapical films. A deep learning algorithm is developed that employes object detection techniques to automatically detect and assign numbers to teeth in dental radiographs. The algorithm achieves a high accuracy in teeth detection and numbering

F. Casalegno et al [20] investigate caries detection with near-infrared trans-illumination (NIRT) using deep learning. A deep learning model is trained on a dataset of NIRT images with known carious lesions. The results show that the model achieves high accuracy in caries detection, providing a promising tool for early caries diagnosis and preventive interventions.

Khetani V. et al. [21] offer a cross-domain analysis of machine learning (ML) and deep learning (DL) techniques, evaluating their impact in diverse domains. The study assesses the use of ML and DL in various fields including healthcare.

Yang Qu et al [22], explore the application of machine learning models for predicting the prognosis of endodontic microsurgery. The researchers utilize machine learning algorithms, including logistic regression, decision trees and random forests, to predict the success or failure of endodontic microsurgery procedures.

Hung M. et al [23] investigate the use of machine learning algorithms for predicting the presence of root caries. The researchers utilize a dataset comprising clinical and radiographic data to train and evaluate machine learning models, such as support vector machines (SVM) and artificial neural networks (ANN). The study demonstrates the potential of machine learning in accurately diagnosing root caries.

Kailai Zhanga et al [24] propose a tooth recognition method based on a label tree with a cascade network structure. The researchers utilize a large dataset of dental images and employ deep learning techniques, including convolutional neural networks (CNN), to achieve accurate teeth recognition and classification. The results demonstrate the effectiveness of the proposed method in automating teeth recognition tasks.

V. Geetha et al [25] focus on the diagnosis of dental caries in X-ray images using the K-Nearest Neighbors (KNN) classifier. The study explores the use of the KNN algorithm to classify dental X-ray images as caries or non-caries. The researchers evaluate the performance of the KNN classifier by considering various features extracted from the X-ray images. The findings highlight the potential of the KNN algorithm in accurately diagnosing dental caries, supporting early detection and prompt treatment.

Noteworthy contributions have also come from Clare Rainey et al [26], Wei Zhan et al [27], Romany F.

Mansour et al [28], Paras Tripathi et al. [29], Lavanya L. et al. [30], Vivek K Verma et al. [31], Jae-Hong Lee et al. [32, 33], Anupama Kalappanavar et al. [34], Sharanjit Kaur et al. [35], Sunali S Khanna et al. [36], Latke and Narawade [37] and Ramzi Ben Ali et al. [38], J. Premkumar [39] among others.

The present study focuses on the importance of pre-processing dental radiographs to sharpen dental boundaries and improve contrast within the images. The aim is to enhance the overall quality of dental X-ray images by employing appropriate pre-processing methods, facilitating accurate diagnosis and treatment planning. Hybrid Ensemble Classifier (HEC) has been used to develop a model that enhances the endodontic treatment by classifying the tooth anomalies into curved canal, narrow canal, long root and calcified root. Stacking technique has been utilized, which combines multiple base classifiers and a meta-classifier to make predictions.

3. Prposed Methodology

The proposed methodology starts by loading the dental image dataset, consisting of images and corresponding labels indicating type of anomaly in the tooth. To augment the dataset, techniques such as rotation, flipping, and scaling are applied, which create variations of the original images. Data augmentation is a widely used technique in machine learning and computer vision to artificially expand the size and diversity of a dataset by applying various transformations to the existing images [40]. Augmenting the data helps to mitigate over-fitting, improve model generalization, and enhance the robustness of the trained model. The five specific augmentation techniques used are;

a. Rotation Range: This augmentation helps simulate different orientations of teeth and enables the model to learn rotation-invariant features.

Random rotation angle = random.uniform(-rotation_range, rotation_range) (1)

b. Shear Range: Shear transformation is performed with a range of 0.2.

Shear angle = random.uniform(-shear_range, shear_range) (2)

c. Zoom Range: The zoom range parameter allows random zooming in or out of images, up to 20%.

Zoom factor = random.uniform(1-zoom_range, 1+zoom_range) (3)

d. Horizontal Flip: The horizontal flip parameter enables random mirroring of images horizontally. This augmentation randomly mirrors the images, simulating the presence of both left and right-oriented teeth.

e. Brightness Range: The brightness range (b_range) parameter controls random adjustment of brightness levels in images within a specified range, between 0.5 and 1.5.

Brightness adjusted = image * random.uniform(b_range[0], b_range[1]) (4)

After data augmentation, the images undergo pre-processing steps, including resizing to a standardized size and converting from BGR to gray-scale. Feature extraction is then performed using the flatten technique to convert the images into one-dimensional feature vectors. These pre-processing steps form the foundation for preparing the dental image dataset for subsequent machine learning tasks. By standardizing the data and extracting relevant features, these steps contribute to improving the quality of the dataset and enable effective training and evaluation of classification models for endodontic treatments. After pre-processing, the dataset is split into training set (80%) and testing set (20%) using the train-test split technique. The train-test split is a crucial step in machine learning to assess the model's performance on unseen data and evaluate its generalization capabilities. By performing the train-test split, we create distinct subsets of data that play different roles in the model development process. The training set enables the model to learn from labelled examples, while the testing set helps evaluate its performance on unseen data. This separation allows us to estimate how well the model is likely to perform in real-world scenarios, providing insights into its effectiveness and potential for refinement.

Several machine learning classifications algorithms are applied to train models for identifying different endodontic challenges, viz. Support Vector Machine (SVM), Naïve Bayes, Decision Tree, K-Nearest Neighbors (KNN), Logistic Regression, XGBoost (Extreme Gradient Boosting). To further improve classification accuracy, a hybrid ensemble classifier is employed. This approach involves training a stacking model with different classifiers such as XGBoost (XGB), Random Forest and Logistic Regression. This ensemble model combines their predictions to make a decision. Finally, the performance of the methodology is analyzed by evaluating the accuracy, precision, recall and F1-score of the classification models. The segmentation results are generated to determine the effectiveness of identifying specific regions of interest. The evaluation and analysis of the models provide valuable insights into the efficacy of the proposed methodology for diagnosis. Figure 3 shows the proposed system architecture.

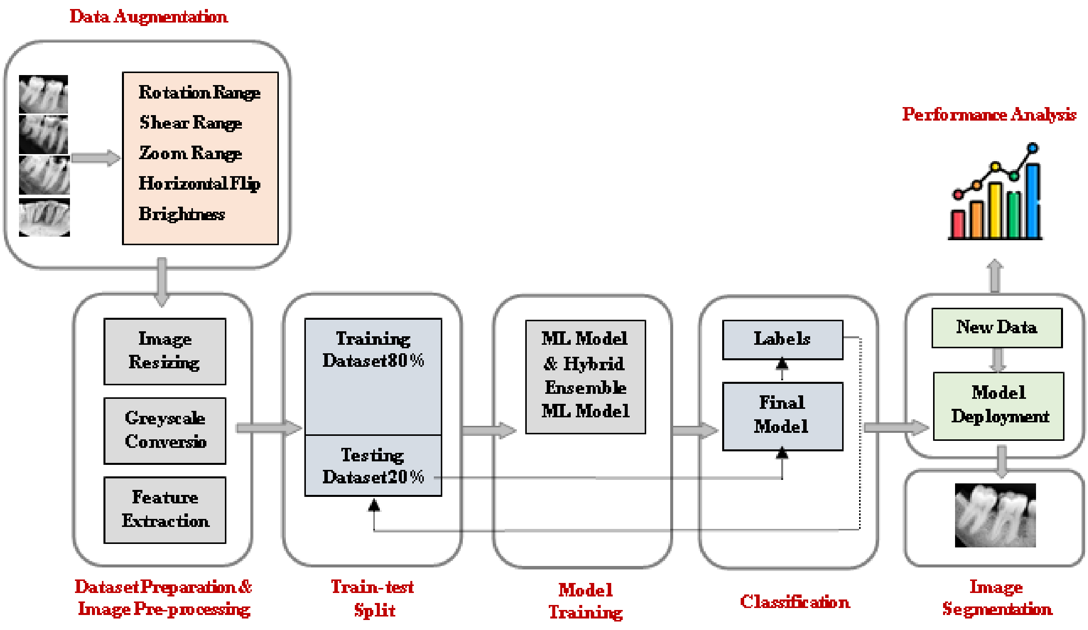


Fig. 3: Proposed system architecture

Hybrid Ensemble Classifier

To create a hybrid ensemble classifier for the user-defined dental image dataset, the stacking technique has been utilized, which combines multiple base classifiers and a meta-classifier to make predictions. An outline of the hybrid ensemble classifier is depicted in Figure 4.

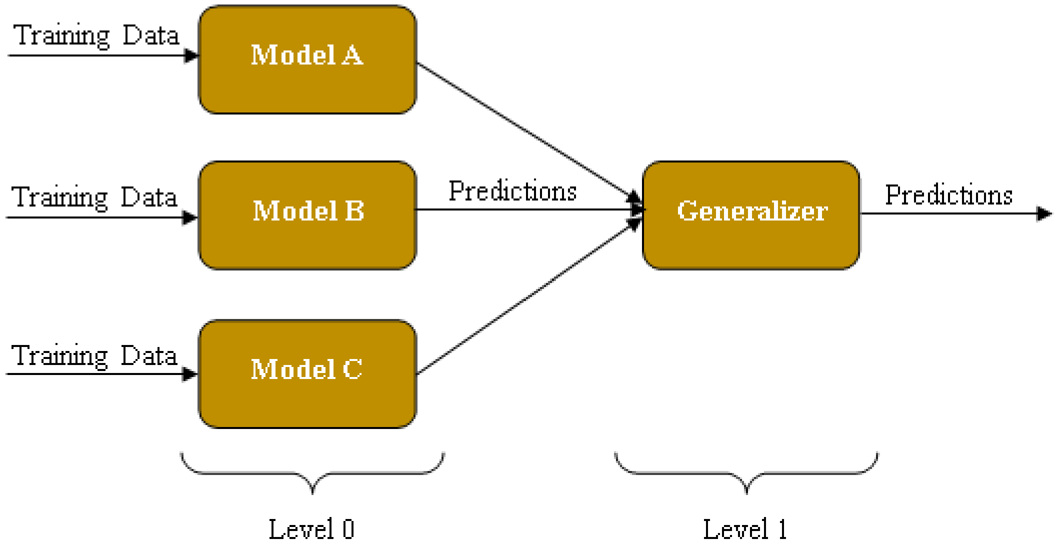


Fig. 4: Hybrid Ensemble Classifier

a. Training with Stacking Model: The stacking model consists of multiple base classifiers, each trained on the training set and a meta-classifier that uses the predictions from the base classifiers as input. Here, the stacking model includes the following base classifiers;

i. xgb.XGBClassifier():

- XGBoost classifier with default settings.

ii. xgb.XGBClassifier(n_estimators=100):

- XGBoost classifier with 100 estimators.

iii. RandomForestClassifier(criterion='entropy', n_estimators=100):

- Random Forest classifier with entropy as the criterion and 100 estimators.

iv. RandomForestClassifier(criterion='gini', n_estimators=100):

- Random Forest classifier with Gini impurity as the criterion and 100 estimators.

Each base classifier is trained on the pre-processed and augmented training set, learning from the generated features and their corresponding labels. The base classifiers aim to capture different aspects and relationships within the data.

b. Testing of Generated Features using Stacking with XGB Classifier: Once the base classifiers are trained, the testing set is passed through each base classifier to obtain predictions. These predictions serve as features for the meta-classifier, which is an XGBoost classifier in this case. The meta-classifier takes the generated features as input and makes the final predictions for the testing set. By utilizing stacking with the XGBoost meta-classifier, the hybrid ensemble classifier combines the strengths of multiple base classifiers to achieve improved classification performance. The stacking technique allows the model to learn from the diverse predictions made by the base classifiers, potentially capturing a more comprehensive representation of the dental image dataset.

The hybrid ensemble classifier created through stacking provides an effective approach to leveraging the strengths of different classifiers and enhancing the accuracy and robustness of endodontic challenge classification.

Image Segmentation

Image segmentation is a crucial task that involves dividing an image into meaningful and distinct regions or objects. Segmentation plays a vital role in isolating specific areas of interest, such as teeth, bone and background, for further analysis and processing (Figure 5). Image segmentation enables specific focus on the regions of interest, aiding in various applications, including diagnosis, treatment planning, and quantitative assessments.

The segmentation is carried out in the steps;

- Maximize Contrast
- Adoptive Thresholding
- Finding Contours
- Taking Negative
- Segmentation

Fig. 5: Image Segmentation

4. Results and Discussion

Experimental Setup

The experimental setup utilized Google Colab, Python and essential libraries such as scikit-learn, matplotlib, numpy and pandas. Google Colab provided a cloud-based Jupyter notebook environment for running Python code and executing machine learning algorithms. Python, along with scikit-learn, facilitated data pre-processing, model training and evaluation. Matplotlib enabled data visualization, while numpy and pandas supported data manipulation and analysis tasks. This setup ensured efficient implementation and analysis of the experimental data.

Performance Parameters

Performance analysis of a classification model involves evaluating metrics such as precision, recall, F1-score, accuracy and the confusion matrix. These metrics provide insights into the model's accuracy, ability to identify positive instances (recall), avoid false positives (precision), overall correctness (accuracy) and a detailed breakdown of classification results (confusion matrix). Assessing these metrics helps understand the model's effectiveness in classifying endodontic challenges and guides further improvements. The performance parameters are defined as;

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

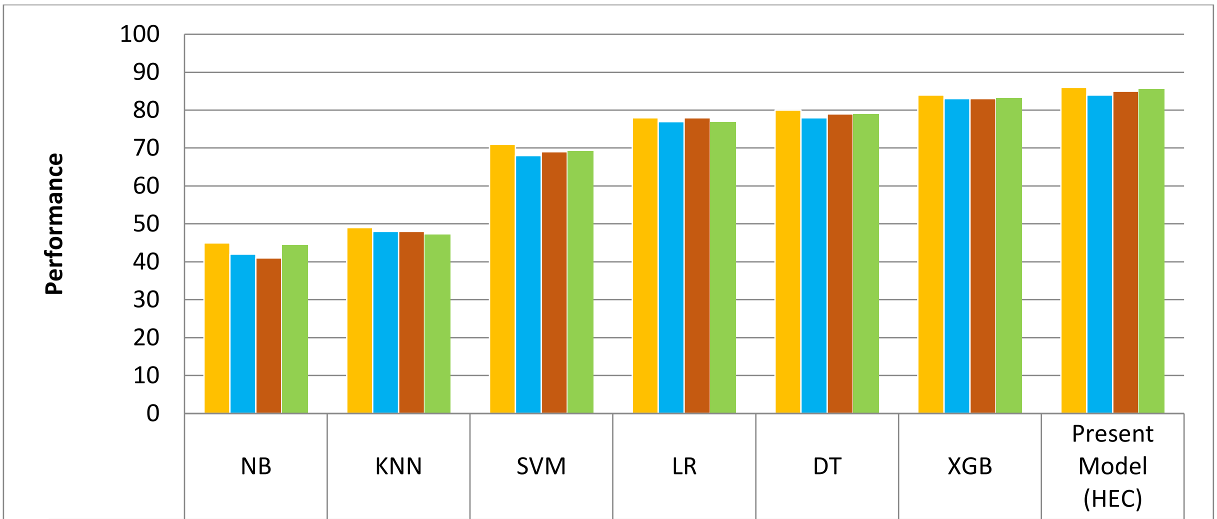
$$\text{Recall} = \frac{TP}{TP + FN} \tag{7}$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

where, TP is true positive, FP is false positive, TN is true negative and FN false negative.

Discussion on Results

In the present research, 900+ real-time Periapical radiographs of each type, calcified roots, curved canal, narrow canal and long root were used to train the model to detect the class of anomaly. Figure 6 shows the comparative analysis of machine learning and proposed algorithms in terms of accuracy, precision, recall and F1-score.



	NB	KNN	SVM	LR	DT	XGB	Present Model (HEC)
Precision	45	49	71	78	80	84	86
Recall	42	48	68	77	78	83	84
F1-Score	41	48	69	78	79	83	85
Accuracy	44.36	47.18	69.19	76.76	78.88	83.09	85.45

Fig. 6: Performance Parameters Comparison of Algorithms

Naive Bayes (NB) has the lowest performance across all metrics. It may not be suitable for this specific classification task. k-Nearest Neighbors (KNN) shows moderate performance but performs better than Naive Bayes. However, it may not be the most optimal choice for imbalanced datasets. Support Vector Machine (SVM), Logistic Regression (LR), Decision Tree (DT) exhibits good performance with high precision, recall, and F1-Score. It is a promising model for the tooth canal type classification task. XGBoost (XGB) demonstrates high performance across all metrics and seems to be a strong contender for the classification task. Hybrid Ensemble Classifier (HEC) appears to perform better in terms of precision, recall, F1-Score, and accuracy than other models.

A confusion matrix is a performance evaluation tool used in classification tasks to assess the accuracy of a model's predictions. It provides a tabular representation of how well the model has classified instances from different classes. The matrix compares the predicted class labels against the true class labels in the dataset. Figure 7 show the confusion matrix diagrams of algorithms used for dental image classification.

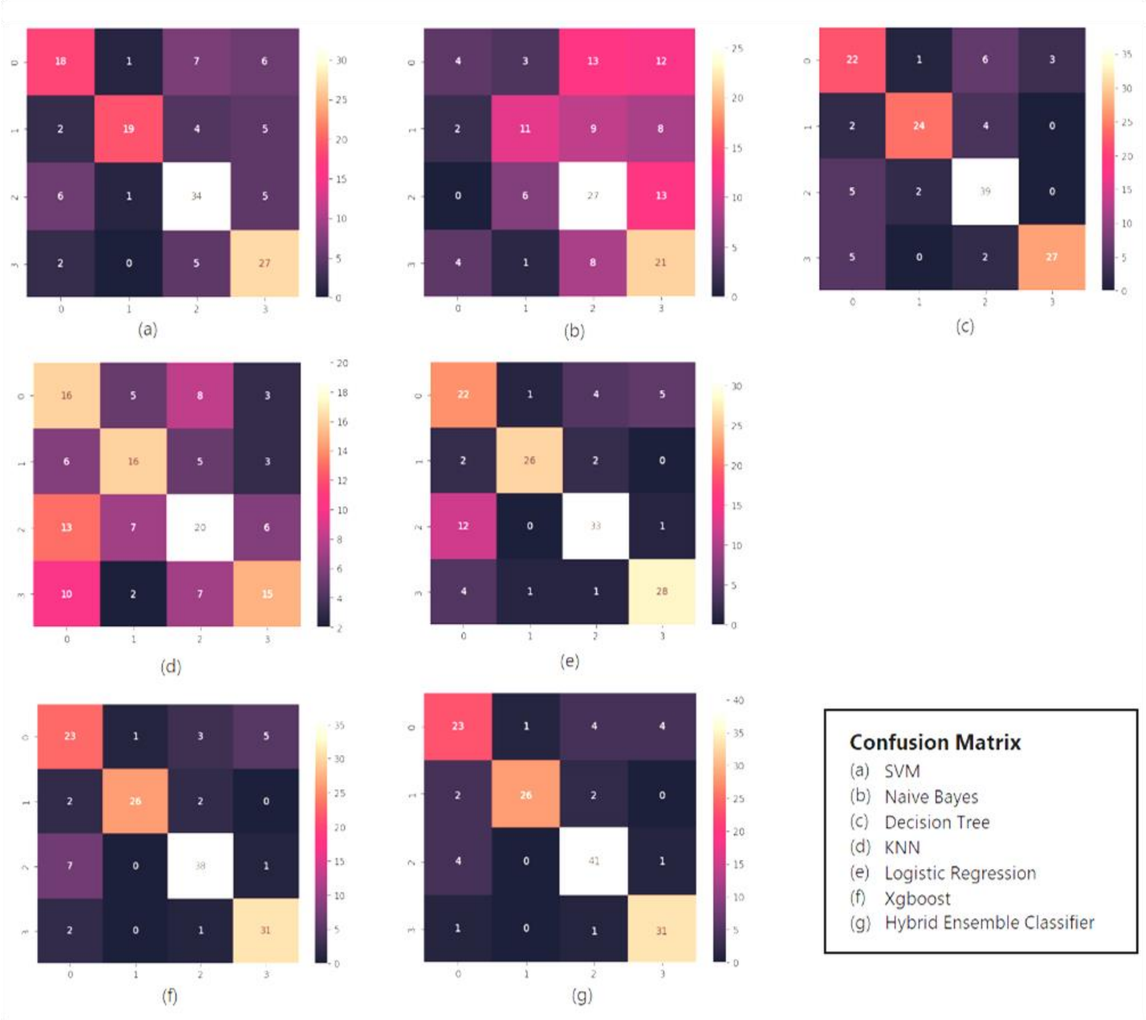


Fig. 7: Confusion Matrix (a) SVM, (b) Naïve Bayes, (c) Decision Tree, (d) KNN, (e) Logistic Regression, (f) XGBoost, (g) Present Model HEC

5. Conclusion

The research addresses the challenges in the root canal treatment posed by curvature, calcification, narrow canal and long root, which can lead to procedural accidents and unfavourable treatment outcomes. The study introduces an innovative approach that leverages AI to enhance endodontic treatments. The key contribution of this research is the development of an HEC, an efficient tool that combines multiple classification algorithms. By harnessing the strengths of these algorithms, HEC significantly improves the accuracy and robustness of classifying various endodontic challenges. This enhancement is crucial in effectively managing intra-radicular infections and improving the overall quality of endodontic procedures. Additionally, the study incorporates image segmentation techniques to isolate specific regions of interest for further analysis. The segmentation process involving contrast enhancement, adaptive thresholding, contour detection and tooth segmentation allows for more precise and targeted examination of the relevant area. Extensive experimentation validates the proposed approach, showcasing notable improvements in precision (86%), recall (84%), F1-score (85%) and accuracy (85.45%). The research offers promising avenues for improving the management of endodontic treatments and achieving better treatment outcomes. By integrating AI and image segmentation techniques, this approach has the potential to improve the way endodontic procedures are carried out, reducing the risks and ensuring more successful treatment. Improvement in data augmentation techniques and creation of a self-generated dataset for training and evaluation, utilization of AI to enhance endodontic treatments through a hybrid ensemble classifier and image segmentation techniques, notable improvements in accuracy and robustness of classifying endodontic challenges, extensive experimental validations supporting the effectiveness of the developed approach, advancements in treatment planning and decision-making processes in the field of endodontics are the key contributions of the present study. The authors are working on evolving the model further to diagnose the difficulty level in the root canal procedure before initiating the treatment, to identify the periapical lesions, to determine the working length of root canal and to predict the success rate of repeat root canal procedure.

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