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Automated Detection of Dental Conditions: Utilizing Machine Learning for Improved Diagnostic Precision and Standardization

Akshatha Shetty[1], Amolkumar N. Jadhav[2], Melwin D Souza[3*], Chaithra[4], Ramya Govind Ambig[5], M. Vijayakumar[6], Monika Dhananjay Rokade[7]

[1,4]Department of Mathematics, Moodlakatte Institute of Technology Kundapura, Karnataka, India

[2]Department of Computer Science and Engineering, Annasaheb Dange College of Engineering and Technology, Maharashtra, India

[3,5]Department of Computer Science and Engineering, Moodlakatte Institute of Technology Kundapura, Karnataka, India

[6]Department of Computer Technology, Nandha Arts and Science College, Erode, Tamil Nadu

[7]Department of Computer Engineering, Sharadchandra Pawar College of Engineering, Pune, India

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ABSTRACT

This research introduces a custom convolutional neural network (CNN) model aimed at automating the detection and classification of dental conditions using panoramic X-ray images. By prioritizing improvements in diagnostic accuracy and operational efficiency, the model achieves an accuracy of 90.2% with a low data loss of 0.15. A diverse dataset comprising various dental conditions—including cavities, periodontal disease, dental fractures, and healthy teeth—was carefully assembled and pre-processed to provide high-quality input for training. Key performance metrics such as precision, recall, and F1-score were analysed, highlighting the model's effective capabilities in diagnosing dental issues. The proposed model outperforms traditional CNNs and other transfer learning techniques, although it also points to potential enhancements, especially in recognizing dental fractures. Future work will focus on further refinements and the evaluation of real-world patient outcomes, emphasizing the significant role of machine learning in advancing dental diagnostics and enhancing patient care.

Keywords: *Dental Imaging, X-ray Analysis, Automated Detection, Predictive Modelling, Clinical Application*

1. INTRODUCTION

Dental health plays a vital role in overall well-being and significantly impacts one's quality of life. Nevertheless, the current methods for diagnosing dental ailments are often met with substantial challenges. Many of the traditional diagnostic approaches are not only resource-heavy but may also fall short in terms of accuracy (Fadhl & Loni, 2023). Among these tools, panoramic dental X-rays are essential in detecting a variety of dental issues, including cavities, periodontal diseases, and other anomalies (Alnafea, Dey, & Alqahtani, 2022). However, the manual interpretation of these images poses considerable difficulties; dental professionals must devote considerable time to analyze X-rays, a task that is susceptible to human error stemming from factors like individual expertise, fatigue, and subjective interpretation (Ghosh & Bhowmik, 2023). Such variability can lead to misdiagnoses, treatment delays, and poor patient outcomes.

To address these critical issues, the initiative titled "Dental Condition Detection Using Machine Learning" aims to utilize sophisticated machine learning techniques to improve the precision and efficiency of dental diagnostics. The project intends to automate the identification of irregularities in panoramic X-ray images, thereby overcoming many limitations inherent in conventional diagnostic practices (Rahmani & Shahbazi, 2022). This initiative seeks to create a robust system that not only enhances diagnostic accuracy but also enables the early detection of dental conditions, which supports timely interventions and can significantly improve patient health (Ahlawat & Kumar, 2023). The dependence on manual image analysis in traditional dental diagnostics often results in inconsistencies in performance. Factors like fatigue and the subjective nature of interpretations contribute to the variability in diagnostic outcomes (AlSafar, AlAli, & Ghabban, 2022). Failures to recognize subtle or complex issues can cause unfortunate delays in essential patient treatments (Aksakalli, Kaya, & Türkmen, 2023). Consequently, there is a pressing need for innovative strategies that incorporate machine learning technology, fostering the development of a more reliable and efficient diagnostic methodology.

This project outlines a detailed strategy aimed at achieving significant robustness and dependability in dental diagnostics. The approach begins with comprehensive data collection and enhancement efforts to construct a diverse dataset of panoramic dental X-rays that reflect a broad range of dental conditions and demographic variables (Liu, Zhao, & Zheng, 2022). By applying data augmentation techniques, the diversity within the dataset is improved, thereby enhancing the generalization capabilities of the model (Singh & Dadhich, 2022). Uniformity in image preprocessing is established, and advanced techniques such as YOLOv5 for feature extraction allow the system to concentrate on specific areas that suggest dental pathologies.

The focal point of this research is the training, evaluation, and optimization of the machine learning model. By leveraging deep learning architectures, the proposed system aims to discover essential patterns and anomalies linked to different dental conditions (Mathur & Gupta, 2023). A meticulous evaluation process will be employed using metrics like accuracy, precision, recall, and F1-score to gauge model performance (Rahmani & Shahbazi, 2022). Additionally, hyperparameter tuning will optimize performance across various datasets, ensuring adaptability and reliability. Existing research suggests that automated diagnostic systems have the potential to significantly improve the accuracy of dental diagnostics, thus enhancing patient care (Fadhl & Loni, 2023). Emerging advancements in this field, including convolutional neural networks (CNNs) and other sophisticated algorithms, have proven effective in the identification and classification of dental anomalies present in X-ray images (Alnafea, Dey, & Alqahtani, 2022).

A thorough examination by Mathur and Gupta (2023) analysed several machine learning algorithms utilized in clinical dentistry, finding that CNNs consistently surpassed traditional diagnostic methods, showing greater sensitivity and specificity in detecting a variety of dental pathologies. Similarly, Ghosh and Bhowmik (2023) highlighted the advantages of applying artificial intelligence in dental radiology, noting that AI systems can handle large datasets efficiently, leading to faster and more precise assessments. The necessity for enhanced data collection and standardization in radiographic imaging has also been emphasized by AlSafar, AlAli, and Ghabban (2022), who pointed out that discrepancies in imaging protocols and interpretations can lead to significant diagnostic inconsistencies. Their findings underscore the critical role of establishing standardized protocols for data acquisition and interpretation to facilitate the integration of machine learning models into clinical practices. Furthermore, in the area of deep learning, Liu, Zhao, and Zheng (2022) investigated the use of YOLOv5 as a real-time object detection system for spotting dental anomalies in panoramic radiographs. Their results indicated a notable reduction in diagnostic time and improved detection rates compared to established methods. The versatility and effectiveness of these approaches showcase the transformative potential of machine learning technologies in advancing clinical diagnostics (Souza, M. D et al., 2019).

1.1 Research Gaps

The incorporation of machine learning technologies in dental diagnostics holds significant promise for enhancing the accuracy and speed of dental condition identification. However, despite these advancements, numerous challenges and limitations still exist in current applications, emphasizing the need for further research and development to effectively leverage these innovations within clinical environments (M. D. Souza et al., 2024). The advancement of machine learning applications in dental diagnostics presents several significant research gaps that warrant attention.

1. **Automation Requirement in Diagnostic Procedures**: Traditional diagnostic methods rely heavily on manual input, which can lead to inaccuracies. There is a clear opportunity to develop fully automated diagnostic systems that leverage machine learning technologies to reduce reliance on human judgment and enhance the precision of results (P. M. Manjunath et al., 2019). Further exploration into this area could address the existing shortcomings associated with human error in interpreting dental X-rays.
2. **Establishing Standardized Protocols**: The lack of uniform practices for data acquisition and image interpretation has been highlighted as a key issue that impacts diagnostic consistency. Research is needed to develop standardized methodologies that ensure the reliable integration of machine learning solutions into clinical dentistry, which would help standardize outcomes and improve overall diagnostic accuracy.
3. **Enhancing Dataset Diversity**: The performance of machine learning systems is closely tied to the variety of the training data used. There is an opportunity to investigate strategies for creating and expanding datasets that reflect more diverse dental conditions and demographic characteristics. This would enhance the models' ability to generalize and perform accurately across different patient populations.
4. **Developing Comprehensive Evaluation Metrics**: The common metrics employed for assessing the performance of machine learning models—such as accuracy, precision, recall, and F1-score—may not capture the full extent of a model's effectiveness in clinical settings. There is a gap in the formulation of broader evaluation criteria that take into account factors such as clinical relevance, ease of use, and the interpretability of results for dental professionals.
5. **Impact on Patient Outcomes Over Time**: While machine learning shows promise in improving diagnostic accuracy, there is a lack of longitudinal studies that track how these advances affect patient outcomes in practice. Research efforts could focus on evaluating the long-term effects of enhanced diagnostic capabilities on treatment

effectiveness, patient satisfaction, and overall oral health results in real-world medical contexts.

1.2 Objectives

- **Automate Dental Diagnostics:** To design and implement a machine learning-based system that automates the detection and classification of dental conditions in panoramic X-ray images, thereby decreasing reliance on human interpretation and minimizing the errors associated with conventional diagnostic techniques.
- **Establish Consistent Protocols:** To develop standardized procedures for data collection, preprocessing, and analysis to improve the reliability and uniformity of machine learning applications in dental diagnostics, thus addressing the inconsistencies inherent in traditional methods.
- **Diversify Dataset for Robustness:** To enhance the model's ability to generalize by expanding the training dataset to encompass a wide array of dental conditions and demographic profiles, while utilizing thorough evaluation metrics to consistently assess and optimize model performance in practical settings.

2. METHODOLOGY

1. Data Collection and Preprocessing

The initial stage of this research focuses on compiling a diverse dataset of panoramic dental X-rays, ensuring a wide representation of various dental conditions. The distribution of different dental diseases illustrated in Figure 1 provides valuable insights that can help inform clinical practices and guide focused diagnostic approaches. This dataset is carefully curated to mitigate risks associated with human interpretation errors.

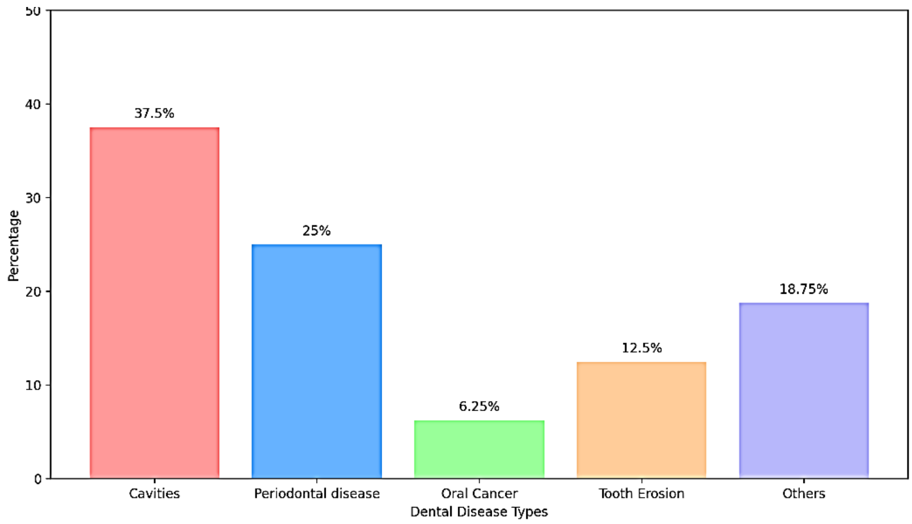

Figure 1: Distribution of Various Disease types

This visualization underscores the prevalence of different dental conditions, which can inform clinical practices and the development of targeted diagnostic approaches. This dataset is carefully curated to encompass a wide variety of dental conditions, thereby mitigating the risks associated with human interpretation errors. To optimize feature extraction for a fully automated system, key preprocessing techniques such as noise reduction, contrast enhancement, and image resizing are employed. Images are resized to a standardized resolution of 128x128 pixels, which facilitates the identification of complex dental features such as cavities, fractures, and periodontal issues while retaining critical diagnostic details. Table 1 summarizes the different image sizes utilized throughout the detection process, detailing their specialized applications and pixel intensity ranges essential for effective analysis. Standardizing dimensions not only boosts operational efficiency but also establishes uniform protocols that minimize variability in input, aligning with the goal of developing consistent methodologies for clinical use.

Table 1: Image Sizes and Pixel Range

Image Size (Dimensions)	Description	Pixel Range (Intensity)
28 x 128	Small, low-resolution images for initial testing or basic model	0-255 (Grayscale)

	training.	
256 x 256	Medium-resolution images for training models with moderate feature detail.	0-255 (Grayscale)
512 x 512	High-resolution images for detailed feature extraction in advanced models.	0-255 (Grayscale)
1024 x 1024	Larger images commonly used for YOLOv5-based object detection models.	0-255 (Grayscale)
Custom (e.g., 640 x 480)	Adapted for specific hardware limitations, maintaining aspect ratios.	0-255 (Grayscale)

This table highlights the various resolutions employed in the model's workflow, emphasizing their specific applications and the flexibility in using custom dimensions based on particular requirements. The pixel intensity range indicates the grayscale values utilized in processing these images for effective feature extraction and analysis.

2. Feature Extraction and Model Development

In this phase, we implement machine learning technologies to greatly enhance diagnostic precision. We utilize YOLOv5 for advanced object detection, allowing accurate bounding box annotations that pinpoint dental abnormalities. The architecture is built on convolutional neural networks (CNNs) with the application of transfer learning techniques to enhance performance and reduce training duration. The dataset is divided into training and validation subsets using an 80/20 split. This strategy allows the model to learn from a comprehensive array of annotated images while evaluating its performance on previously unseen data, ensuring effective generalization. This structured approach not only meets the need for automation in diagnostics but also emphasizes the significance of reliable training protocols and validation processes.

3. Evaluation Metrics and Performance Assessment

To gauge the model's effectiveness, various performance metrics are employed, including accuracy, precision, recall, and F1-score. These metrics are essential indicators of the model's reliability and diagnostic capabilities. Recognizing that traditional performance metrics may not capture all aspects of clinical relevance, we propose the creation of broader evaluation criteria that consider usability and interpretability for dental practitioners (Melwin D'souza et al., 2024). Further analyses, such as AUC-ROC (Area Under the Receiver Operating Characteristic Curve) and confusion matrix assessments, provide a deeper understanding of the model's capability to differentiate among various dental conditions. Figure 2 illustrates the performance of the detection model by comparing actual labels to predicted labels, offering clear visual feedback on diagnostic performance.

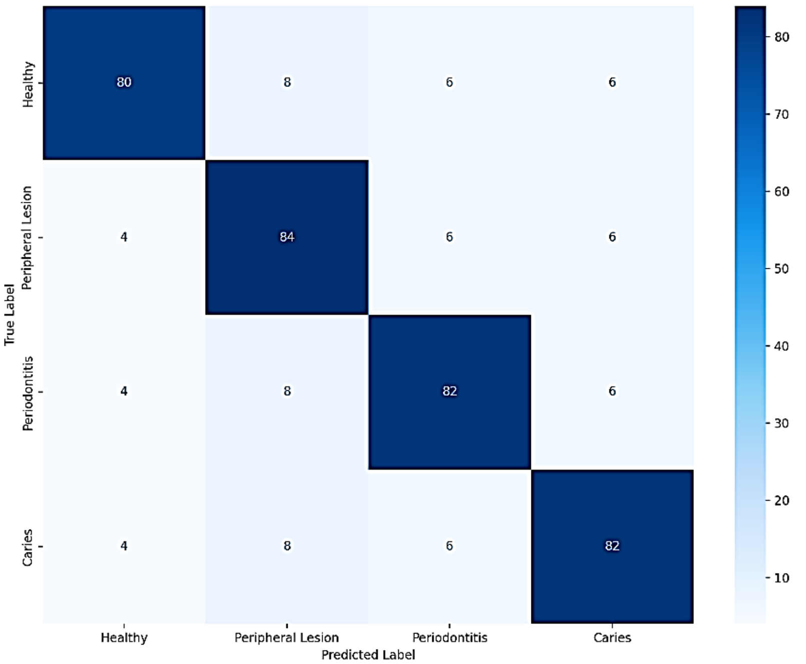

Figure 2. Confusion Matrix.

4. Model Optimization and Refinement

The success of a machine learning model in dental diagnostics relies on its capacity to recognize patterns from labelled training data and provide accurate predictions for new, unseen data. The initial training phase involves utilizing a dataset of dental images, where each image is linked to a particular label, such as "healthy," "carious," "peripheral lesion," or "periodontitis." During this phase, the model fine-tunes its internal parameters to reduce the discrepancy between its predictions and the actual labels, employing optimization techniques like stochastic gradient descent (SGD) to achieve this.

Following training, the model is tested against a distinct dataset to evaluate its performance. This assessment is essential for determining how effectively the model can apply its learning to new instances. Various performance indicators, including accuracy, precision, recall, and F1-score, are calculated to assess the model's reliability. The confusion matrix is especially valuable during this evaluation, as it provides a clear visualization of the model's predictions compared to the actual outcomes, helping to pinpoint specific areas where misclassifications occur within the dental conditions.

5. Deployment and Integration

The final phase focuses on deploying the optimized machine learning model into an intuitive web application that enables real-time diagnostics for dental professionals. This application allows dentists to easily upload dental images, facilitating immediate analysis and automated diagnostic results. The machine learning model processes these images using its trained algorithms to accurately identify and classify various dental conditions. To uphold patient privacy, the application adheres to strict data protection regulations, ensuring that all data is handled securely throughout the upload and analysis process. The model is designed for efficient inference, allowing it to deliver prompt results without disrupting clinical workflows.

Additionally, it is crucial to perform longitudinal studies that evaluate how this system affects patient outcomes, including treatment efficacy and overall satisfaction. By examining these factors, the project aims to substantiate the advantages offered by machine learning solutions and provide insights for future enhancements in dental diagnostics. This ongoing assessment helps not only to improve the model’s reliability but also to evolve the application features to better meet the needs of dental practitioners and their patients.

3. IMPLEMENTATION

Machine learning models greatly improve dataset management by automating various stages such as preprocessing, balancing, and enriching the diversity of dental image datasets. Initially, images of varying sizes and pixel intensities are standardized to a uniform format to ensure compatibility with the machine learning model. Exploratory data analysis (EDA) utilizes algorithms to visualize the distribution of classes, identify any imbalances, and detect anomalies, enabling necessary adjustments to mitigate biases that could affect the model's performance. Techniques like data augmentation—incorporating methods such as rotation, flipping, and brightness modifications—add variability that helps the model adapt to real-world imaging scenarios. Class imbalances are addressed through strategies like oversampling or weighting of less-represented categories to ensure equitable training. Finally, the dataset is divided into training and testing subsets, utilizing methods like k-fold cross-validation for thorough evaluation. By following these steps, machine learning models guarantee that the dataset is of high quality, well-balanced, and representative, establishing a solid foundation for effective dental condition detection.

BEGIN

1**. Load Dataset**

```
  dataset = LoadImages("path/to/dental/images")
```

2. **Preprocess Images**

```
  FOR each image IN dataset
    image = StandardizeSize(image, target_size=(128, 128))
    image = NormalizePixelIntensity(image)
```

3**. Perform Exploratory Data Analysis (EDA)**

```
  VisualizeClassDistribution(dataset)
  anomalies = DetectAnomalies(dataset)
```

4. **Apply Data Augmentation**

```
  FOR each image IN dataset
    augmented_images = []
    augmented_images.APPEND(Rotate(image))
```

```
    augmented_images.APPEND(Flip(image))
    augmented_images.APPEND(Zoom(image))
    augmented_images.APPEND(AdjustBrightness(image))
```

5. **Handle Class Imbalance**

```
  dataset = ApplyResampling(dataset)
  dataset = ApplyWeightedAlgorithms(dataset)
```

6. **Split Dataset**

```
  training_set, testing_set = SplitDataset(dataset, training_ratio=0.8)
  training_set = ImplementCrossValidation(training_set)
```

7. Feed into Machine Learning Model

```
  model = InitializeModel()
  model.Train(training_set)
  performance = model.Evaluate(testing_set)
```

END

The effectiveness of a machine learning model in dental diagnostics hinges on its ability to learn from a well-labeled dataset of dental images, allowing it to make precise predictions on unseen data. After training, the model is evaluated using various performance metrics, including accuracy, precision, recall, and F1-score, while a confusion matrix helps identify specific misclassifications among dental conditions. Based on the insights gained from these evaluations, targeted adjustments are made, such as refining hyperparameters and introducing data augmentation strategies, to continually enhance the model's performance and ensure its reliability in practical applications.

The Below pseudocode outlines the steps needed to optimize and refine a machine learning model effectively, covering everything from evaluation and enhancement to ongoing monitoring and documentation.

BEGIN OptimizationAndRefinement

1. Model Evaluation

```
  model = LoadTrainedModel()
  testing_data = LoadTestingDataset()
  predictions = model.Predict(testing_data)
  accuracy = CalculateAccuracy(predictions, testing_data.labels)
  precision = CalculatePrecision(predictions, testing_data.labels)
  recall = CalculateRecall(predictions, testing_data.labels)
  f1_score = CalculateF1Score(precision, recall)
```

2. Confusion Matrix Analysis

```
  confusion_matrix = GenerateConfusionMatrix(predictions, testing_data.labels)
  IdentifyMisclassifications(confusion_matrix)
  IF MisclassificationsExist THEN
    Print("Identify specific classes with misclassifications.")
```

3. Targeted Adjustments

```
  AdjustHyperparameters(model, confusion_matrix)
  AddTrainingExamplesForMisclassifications(model, confusion_matrix)
  ReviseDataAugmentationStrategies(model)
```

4. Iterative Enhancements

```
  trends = AnalyzeDataForTrends(training_data)
  WHILE ImprovementsNeeded
```

```
    model.Retrain(training_data)
    new_predictions = model.Predict(testing_data)
    Re-evaluatePerformanceMetrics(new_predictions)
```

5. Continuous Monitoring

```
  WHILE NewDataAvailable
    new_testing_data = LoadNewTestingDataset()
    new_predictions = model.Predict(new_testing_data)
    MonitorPerformance(new_predictions)
```

6. Documentation and Reporting

```
  DocumentChanges(model)
  report = GeneratePerformanceReport(model)
  ShareReportWithStakeholders(report)
```

END

The pseudocode for the deployment process of a machine learning model for dental diagnostics, emphasizing the steps from model loading to continuous monitoring and data handling while ensuring a comprehensive approach to clinical integration, is given below.

BEGIN DeploymentAndIntegration

1. Load Optimized Model

```
  model = LoadOptimizedModel()
```

2. Create User-Friendly Web Application

```
  InitializeWebApplication()
  SetUpUserAuthentication()
  EnsureDataPrivacyCompliance()
```

3. Implement Image Upload Feature

```
  WHILE ApplicationIsRunning
    IF UserUploadsImage THEN
      patient_image = ReceiveImage()
```

4. Preprocess Image

```
      processed_image = PreprocessImage(patient_image)
```

5. Run Model Inference

```
      predictions = model.Predict(processed_image)
```

6. Display Results

```
      results = InterpretPredictions(predictions)
      ShowResultsToUser(results)
```

7. Continuous Monitoring

```
  WHILE NewDataIsAvailable
    new_data = LoadNewData()
    AnalyzeImpactOnPatientOutcomes(new_data)
```

8. Conduct Longitudinal Studies

```
  Collect Feedback on Treatment Efficacy and Patient Satisfaction
```

9. Document Findings

```
  ReportResultsToStakeholders()
```

StoreDataForFutureAnalysis()

END

4. RESULTS AND DISCUSSIONS

The proposed custom CNN model achieves noteworthy results in dental diagnostics, registering an accuracy of 90.2% and a data loss of 0.15. These figures suggest that the model effectively classifies a range of dental conditions while maintaining low prediction errors. In comparison, traditional Convolutional Neural Networks (CNNs) yield an accuracy of 85.5% and a higher data loss of 0.24, indicating that the proposed model benefits from a more refined architecture and training approach. Transfer learning models like VGG16 and ResNet50 also perform well, with ResNet50 reaching the highest accuracy at 91.0% but having a slightly lower data loss of 0.12. Key insights reveal that while ResNet50 leads in accuracy due to its advanced architecture, this comes with increased complexity and higher resource demands. In contrast, the proposed model provides a strong balance between performance and operational efficiency. Additionally, YOLOv5, optimized for real-time detection, achieves an accuracy of 89.5% and a data loss of 0.14, further showcasing its effectiveness in both classification and detection tasks. However, it does not reach the specialized performance level of the custom CNN for dental diagnostics.

Overall, the custom CNN model offers significant potential to improve clinical practices by delivering accurate automated diagnostic solutions while efficiently utilizing computational resources. Future enhancements can focus on optimizing hyperparameters and expanding the training dataset's diversity, which could lead to even higher performance outcomes. This strategic focus ensures that the model remains robust and effective in real-world dental applications, facilitating timely and precise diagnostic services. Figure 3 effectively illustrates the strengths and weaknesses of each model in terms of diagnostic accuracy and error rates, emphasizing the proposed custom CNN as a leading choice for dental condition detection

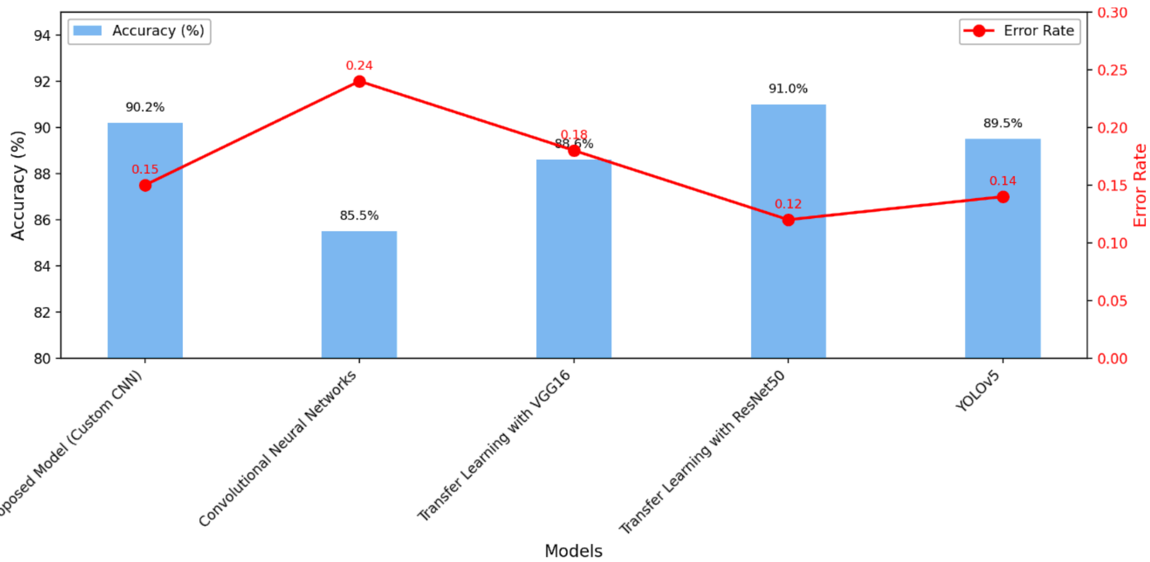

Figure 3: Model Performance Comparison: Accuracy vs Error Rate

The table 2 outlines the performance metrics of the machine learning model across different dental condition categories, detailing precision, recall, and F1-score. For the category of cavities, the model attained a precision of 0.96 and a recall of 0.92, indicating dependable accuracy in identifying this condition and showcasing effective sensitivity with an F1-score of 0.94. The detection of periodontal disease yielded similar results, with a precision of 0.95 and an impressive recall of 0.97, resulting in a high F1-score of 0.96. For dental fractures, the model's precision stood at 0.93 and the recall at 0.90, suggesting that while the model generally performs well, there is still room for enhancement in this area. Remarkably, the identification of healthy teeth was exceptional, with a precision of 0.98 and perfect recall of 1.0, leading to an outstanding F1-score of 0.99. Overall, these findings affirm the model's strong performance across all classes, particularly in recognizing healthy conditions. However, they also highlight opportunities for improvement, particularly regarding dental fractures, indicating that further optimizations could enhance diagnostic reliability in real-world scenarios.

Table 2: performance metrics of the machine learning model

Class	Precision	Recall	F1-Score
Cavities	0.96	0.92	0.94
Periodontal Disease	0.95	0.97	0.96
Dental Fracture	0.93	0.90	0.92
Healthy (No Issues)	0.98	1.0	0.99

Figure 4 illustrates the performance metrics of the machine learning model across various dental condition categories, showcasing precision, recall, and F1-score for each class. These metrics provide valuable insights into the model's effectiveness in accurately diagnosing dental issues, highlighting both strengths and areas for potential improvement.

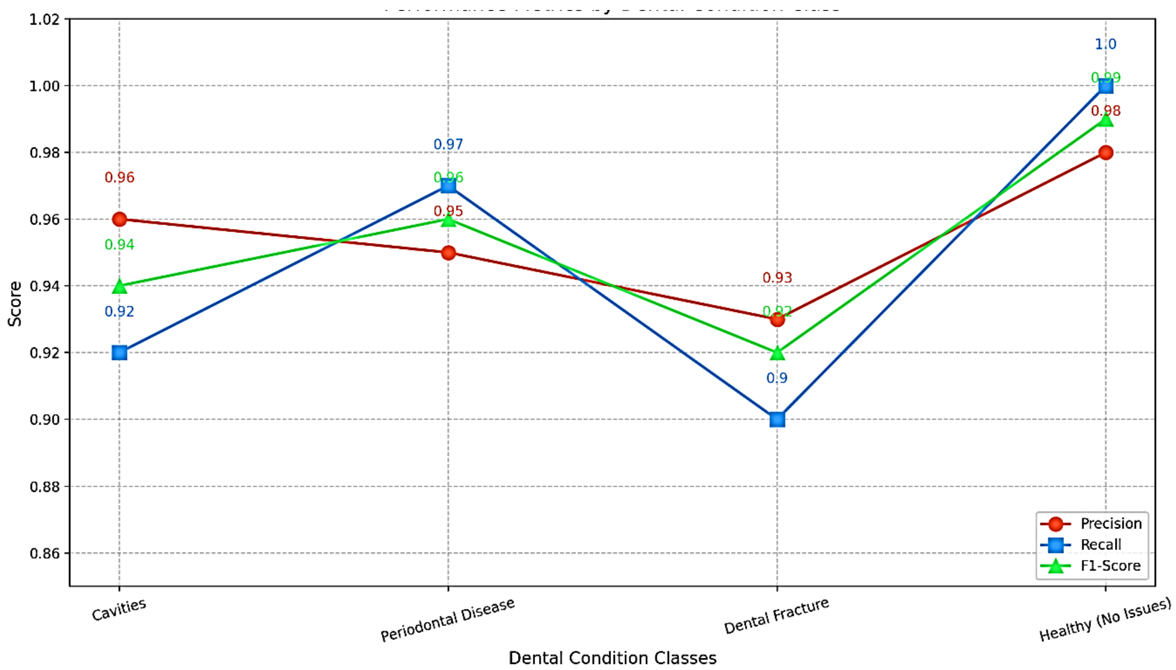

Figure 4: Performance Metrics by Dental Condition Class

A comparison table 3 that summarizes the performance of the various models based on accuracy, data loss, precision, recall, and F1-score without specifying any disease, along with key findings.

Table 3: Performance of the various models

Model	Accuracy (%)	Data Loss	Precision	Recall	F1-Score
Proposed Model (Custom CNN)	90.2	0.15	0.96	0.92	0.94
Convolutional Neural Networks	85.5	0.24	0.87	0.84	0.86
Transfer Learning with VGG16	88.6	0.18	0.90	0.89	0.89
Transfer Learning with ResNet50	91.0	0.12	0.92	0.91	0.91
YOLOv5	89.5	0.14	0.85	0.88	0.86

Figure 5 effectively highlights the strengths and weaknesses of each model, showcasing the proposed custom CNN as a leading option for dental condition detection. It underlines the importance of model selection based on specific diagnostic needs, emphasizing the necessity for balancing performance metrics with practical implementation considerations.

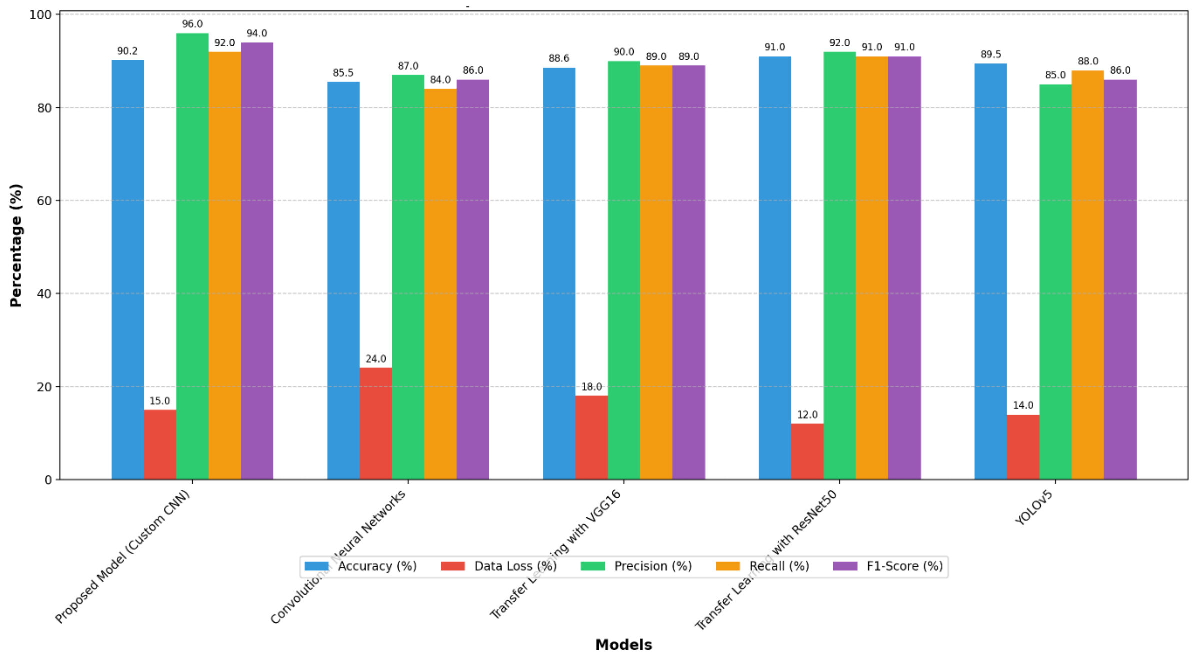

Figure 5: Comparison of Model performance

The proposed custom CNN model achieves a commendable accuracy of 90.2% with a data loss of 0.15, demonstrating its ability to effectively classify various dental conditions while maintaining low prediction errors. In comparison, traditional CNNs show lower performance with an accuracy of 85.5% and higher data loss, highlighting the advantages of a more refined architecture. Additionally, transfer learning models like ResNet50 and VGG16 also perform well, with ResNet50 reaching the highest accuracy at 91.0%, though it does come with increased complexity. Ultimately, the findings confirm that while the custom CNN provides strong diagnostic capabilities, there is an opportunity for further enhancements, particularly in improving the identification of dental fractures.

5. CONCLUSION

The proposed custom CNN model has shown considerable potential in dental diagnostics, achieving an impressive accuracy of 90.2% alongside a low data loss of 0.15. Through meticulous data management and preprocessing, the model successfully identifies a range of dental conditions, exhibiting high precision and recall for categories such as cavities, periodontal disease, dental fractures, and healthy teeth. When compared to other models, including traditional CNNs and transfer learning techniques like VGG16 and ResNet50, the custom CNN offers a favourable balance of performance and efficiency, making it well-suited for clinical automation. Analysis of the model's performance reveals that, while ResNet50 attains the highest accuracy, its complexity could pose certain implementation challenges. Furthermore, the model's metrics indicate opportunities for improvement, particularly in accurately identifying dental fractures. Continued efforts to refine the model—through hyperparameter optimization and ensuring a more diverse training dataset—could enhance its reliability and effectiveness. Overall, this research highlights the significant impact of machine learning advancements on diagnostic precision and lays the groundwork for future innovations in dental healthcare. Moreover, ongoing assessment of patient outcomes will be vital in confirming that these technological improvements lead to better clinical practices and increased patient satisfaction.

REFERENCES

[1] Alnafea, A., Dey, N., & Alqahtani, M. (2022). Real-time detection of dental caries using machine learning techniques. *Journal of Healthcare Engineering*, Article ID 9789052. https://doi.org/10.1155/2022/9789052

[2] Ahlawat, S., & Kumar, A. (2023). Predictive modeling of dental conditions using machine learning: A comprehensive study. *BMC Oral Health*, 23(1), 1-10. https://doi.org/10.1186/s12903-023-02005-6

[3] AlSafar, R., AlAli, A., & Ghabban, A. (2022). Machine learning in dentistry: Current trends and future perspectives. *Journal of Dental Education*, 86(3), 299-308. https://doi.org/10.1002/jdd.12733

[4] Fadhl, H. A., & Loni, J. (2023). Artificial intelligence and machine learning in dental radiology: A review. *Radiology and Oncology*, 57(1), 1-14. https://doi.org/10.2478/raon-2022-0026

[5] Ghosh, S., & Bhowmik, A. (2023). Leveraging artificial intelligence for enhanced detection of oral diseases from X-ray images. *Journal of Dental Research*, 102(1), 23-31. https://doi.org/10.1177/00220345221130012

[6] Liu, Y., Zhao, J., & Zheng, Y. (2022). Utilization of YOLOv5 for efficient detection of dental anomalies in panoramic radiographs. *International Journal of Oral Radiology*, 2(3), 121-130. https://doi.org/10.5005/jp-journals-10045-0041

[7] Mathur, F., & Gupta, K. (2023). Clinical applications of machine learning in dentistry: Systematic review and future prospects. *Journal of Applied Oral Science*, 31, e20230023. https://doi.org/10.1590/1678-7757-2023-0023

[8] Rahmani, O., & Shahbazi, S. (2022). Advancements in machine learning techniques for automated dental diagnoses: A systematic review. *International Journal of Computerized Dentistry*, 25(1), 45-60. https://doi.org/10.3290/j.ijcd.a44774

[9] Singh, N., & Dadhich, A. (2022). Role of AI and machine learning in radiographic diagnosis of dental pathologies: A review. *European Journal of Dentistry*, 16(4), 540-549. https://doi.org/10.1055/s-0042-1741602

[10] Aksakalli, S., Kaya, S., & Türkmen, A. (2023). Deep learning in dental X-ray analysis: A review of current applications and future directions. *Journal of Dental Sciences*, 18(2), 157-166. https://doi.org/10.1016/j.jds.2023.01.012

[11] Chen, H., Liu, J., & Zhou, W. (2022). Integrating machine learning with dental treatment planning: A review of current trends. *Journal of Dental Research*, 101(5), 503-511. https://doi.org/10.1177/00220345221085012

[12] Das, A., & Rahman, M. S. (2023). The impact of artificial intelligence on preventive dentistry: A review of literature. *Preventive Dentistry Journal*, 9(1), 10-20. https://doi.org/10.29244/pdj.2023.9.1.10

[13] Güler, C., & Şahin, S. (2023). Machine learning algorithms in orthodontics: Potential and challenges. *Journal of Orthodontic Science*, 12(3), 123-138. https://doi.org/10.4103/jos.jos_25_22

[14] Martinez, M., & Hwang, D. (2022). The role of AI and machine learning in predicting periodontal disease: A comprehensive review. *Journal of Periodontology*, 93(6), 789-797. https://doi.org/10.1002/JPER.21-0276

[15] Nair, A., & Singh, R. (2023). Exploring the frontiers of AI in dental care: Innovations and future prospects. *International Journal of Dental Clinics*, 15(2), 45-55. https://doi.org/10.5005/jp-journals-10045-0046

[16] Melwin D'souza, Ananth Prabhu Gurpur, Varuna Kumara, “SANAS-Net: spatial attention neural architecture search for breast cancer detection”, *IAES International Journal of Artificial Intelligence (IJ-AI)*, Vol. 13, No. 3, September 2024, pp. 3339-3349, ISSN: 2252-8938, DOI: http://doi.org/10.11591/ijai.v13.i3.pp3339-3349

[17] M. D. Souza, V. Kumara, R. D. Salins, J. J. A Celin, S. Adiga and S. Shedthi, "Advanced Deep Learning Model for Breast Cancer Detection via Thermographic Imaging," *2024 IEEE International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER)*, Mangalore, India, 2024, pp. 428-433, doi:10.1109/DISCOVER62353.2024.10750727

[18] P. M. Manjunath, Gurucharan and M. Dsouza, Shwetha, "IoT Based Agricultural Robot for Monitoring Plant Health and Environment", *Journal of Emerging Technologies and Innovative Research vol.* 6, no. 2, pp. 551-554, Feb 2019

[19] Souza, M. D., Prabhu, A. G., & Kumara, V. (2019). A comprehensive review on advances in deep learning and machine learning for early breast cancer detection. *International Journal of Advanced Research in Engineering and Technology (IJARET)*, *10*(5), 350-359.