DEEP LEARNING-BASED MULTICLASS CLASSIFICATION FOR DENTAL DISEASE DETECTION USING DENSENET-201

18ECP107L- MINOR PROJECT

A PROJECT REPORT

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in partial fulfillment for the award of the degree

of

BACHELOR OF TECHNOLOGY

in

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

COLLEGE OF ENGINEERING AND TECHNOLOGY

SRM INSTITUTE OF SCIENCE & TECHNOLOGY
(Deemed to be University u/s 3 of UGC Act, 1956)

SRM INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)

SRM NAGAR, KATTANKULATHUR-603203,

CHENGALPATTU DISTRICT

NOVEMBER 2024

SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

(Under Section 3 of UGC Act, 1956)

BONAFIDE CERTIFICATE

Certified that this project report titled "**DEEP LEARNING-BASED MULTICLASS CLASSIFICATION FOR DENTAL DISEASE DETECTION USING DENSENET-201**" is the bonafide work of "**SHERON S [Reg No: RA2111004010168], NEHAL SREEJITH [Reg No: RA2111004010294], ADITHYA B CHANDRAN [Reg No: RA2111004010328],** who carried out the 18ECP107L-Minor Project work under my supervision. Certified further, that to the best of my knowledge, the work reported herein does not form any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

The Dental diseases, such as gingivitis, tooth discoloration, mouth ulcers, cavities, and calculus, are prevalent globally and pose significant challenges to oral health. Early detection of these conditions can prevent severe complications, yet traditional diagnostic methods rely heavily on visual examination, which can be subjective and prone to error. In recent years, the advent of deep learning has opened new possibilities in medical imaging and automated diagnosis, leading to more precise and consistent results. This research focuses on developing a multiclass classification model using the DenseNet-201 architecture to automatically detect five classes of dental diseases from a dataset of 1,500 intraoral images.

The DenseNet-201 model was chosen for its ability to efficiently utilize feature propagation through dense connections, making it highly suitable for medical imaging tasks. The dataset comprised 300 images per class, categorized into five groups corresponding to the dental diseases being studied. Preprocessing techniques, including resizing and normalization, were applied to ensure uniformity in the input data, and a soft-max activation function was used for the final layer to enable multiclass classification.

The model achieved an accuracy of 96%, outperforming several existing approaches, including the InceptionResNetV2 model, which achieved 94% under similar testing conditions. Evaluation metrics such as accuracy, ROC curves, and AUC scores were employed to validate the performance of the model. The results indicate that the DenseNet-201-based model can be a reliable tool for the automatic detection of dental diseases, offering a significant improvement over manual diagnostic methods. However, further work is needed to enhance the model's generalization capabilities, particularly in diverse clinical settings.

This study highlights the potential of deep learning, particularly DenseNet-201, in advancing dental diagnostics by providing a scalable and accurate solution for early disease detection. The findings have significant implications for clinical practice, where automated diagnostic tools can assist dental professionals in delivering timely and accurate diagnoses, ultimately improving patient outcomes. Future research will focus on integrating the model into real-time diagnostic systems and exploring additional datasets to improve its robustness and applicability in various healthcare environments.

ACKNOWLEDGEMENT

We would like to express our deepest gratitude to the entire management of SRM Institute of Science and Technology for providing me with the necessary facilities for the completion of this project.

I wish to express my deep sense of gratitude and sincere thanks to our Professor and Head of the Department **Dr. SANGEETHA M**, for her encouragement, timely help, and advice offered to me.

I am very grateful to my guide **Dr. S. MURUGAVENI** Assistant Professor, Department of Electronics and Communication Engineering, who has guided me with inspiring dedication, untiring efforts, and tremendous enthusiasm in making this project successful and presentable.

I would like to express my sincere thanks to the project coordinator **Dr. SANDEEP KUMAR P** for her time and suggestions for the implementation of this project.

I also extend my gratitude and heartful thanks to all the teaching and non-teaching staff of the Electronics and Communications Engineering Department and to my parents and friends, who extended their kind cooperation using valuable suggestions and timely help during this project work.

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ABBREVIATIONS

1. CNN – Convolutional Neural Network
2. DL – Deep Learning
3. ReLU – Rectified Linear Unit
4. ROC – Receiver Operating Characteristic
5. AUC – Area Under Curve
6. IoU – Intersection over Union
7. TP – True Positive
8. FP – False Positive
9. TN – True Negative
10. FN – False Negative
11. SVM – Support Vector Machine
12. ML – Machine Learning
13. VGG – Visual Geometry Group (network architecture)
14. DCNN – Deep Convolutional Neural Network
15. DenseNet – Densely Connected Convolutional Networks
16. ResNet – Residual Network
17. CT – Computed Tomography
18. MRI – Magnetic Resonance Imaging

CHAPTER 1

INTRODUCTION

Dental diseases are something almost everyone deals with at some point in their lives. From tooth discoloration to gingivitis, mouth ulcers, cavities, and calculus, these issues are more than just cosmetic—they can lead to serious health problems like heart disease, diabetes, and respiratory infections if not addressed [1], [2]. Traditionally, diagnosing these conditions has been a process that relies heavily on the expertise of dental professionals. But despite their skills, this method can be slow and prone to human error due to the complexity and variability of the diseases being examined [3]. As the demand for faster, more accurate diagnoses grows, there is a clear need for innovative solutions that can help both clinicians and patients. This is where Artificial Intelligence (AI) steps in, offering a new way to revolutionize how we approach dental diagnostics.

Over the past few years, AI has made significant strides across many areas of healthcare, and dentistry is no exception. Deep learning technologies like Convolutional Neural Networks (CNNs) have shown impressive potential in automating the analysis of dental images, including radiographs, intraoral photographs, and orthopantomograms (OPGs) [4], [5]. By teaching machines to recognize patterns in images, these AI models can detect dental diseases with incredible accuracy—often spotting issues that even experienced clinicians might miss. Among the various AI architectures, DenseNet and ResNet have emerged as particularly effective at handling complex image classification tasks. And when combined with techniques like transfer learning, they become even more powerful, especially when the available dataset is small or not well-balanced [6], [7].

Transfer learning is a particularly exciting aspect of AI's role in dentistry. It allows deep learning models to learn from large, general datasets (like ImageNet) and then adapt this knowledge to a specific task, such as dental disease detection. This is crucial in dentistry, where collecting large amounts of labled data is often difficult. Thanks to transfer learning, AI models can be trained with relatively small datasets and still achieve impressive performance [8]. For example, AI models have been trained to detect gingivitis from intraoral photos or identify cavities, tooth decay, and periodontal disease from panoramic Xrays [8], [9]. These breakthroughs demonstrate just how much potential AI has in helping us improve dental care.

But AI in dentistry isn't just about classifying diseases—it also holds great promise for predicting the progression of these conditions. Instead of simply identifying current issues, AI could help predict how a dental condition might worsen over time. For example, AI could flag areas at high risk of developing cavities or predict how gingivitis might progress into more severe periodontal disease. These predictive capabilities could shift the focus from reactive to proactive care, allowing dental professionals to intervene earlier and prevent serious issues down the road. This could ultimately improve patient outcomes and reduce the long-term costs associated with treating advanced dental diseases.

Another fascinating area for AI in dentistry is its ability to handle multiple types of data. By combining not just images but also patient history and other clinical data, AI can provide a much more comprehensive diagnosis. Studies have already shown that AI models trained on both clinical data and radiographs are more accurate than those trained on images alone [12], [13]. For example, if an AI system had access to a patient's age, medical history, and lifestyle habits, along with their X-rays, it could make much more informed predictions about their dental health. This approach could lead to more personalized, patient-specific treatments and improve overall diagnostic accuracy.

DenseNet-201, the model at the core of this study, is particularly well-suited for these kinds of tasks. Its dense connections between layers allow it to extract features from images efficiently and make highly accurate predictions [6], [10]. But even with such a powerful model, there are challenges to consider. Dental datasets are often small and may not fully capture the variety of real-world conditions. To address this, advanced techniques like data augmentation—random cropping, colour jittering, and flipping—are used to create more diverse training data. This helps ensure that the model is not just learning to classify images from a single dataset but can generalize to a wider variety of images in real-world settings.

Despite the promise of AI, there are still obstacles to overcome, particularly when it comes to obtaining high-quality labled dental data. Annotated datasets are expensive and timeconsuming to create, and not every clinic or researcher has access to them. However, new techniques, like synthetic data generation, are helping to address this challenge. By generating artificial images that resemble real-world dental conditions, researchers can train AI models without relying solely on expensive labled data [14]. This is a key step forward in making AI in dentistry more accessible and effective.

While most studies on AI in dentistry have focused on classifying diseases, this research goes a step further by also exploring AI’s predictive capabilities. By training a DenseNet201 model to detect five common dental diseases—such as tooth discoloration, gingivitis, mouth ulcers, cavities, and calculus—this study aims to improve both diagnostic accuracy and predict disease progression. The goal is to create a tool that not only identifies current dental issues but also predicts potential future risks, giving dental professionals a more powerful, proactive tool to improve patient care. By using data augmentation techniques, this study also strives to make the model more adaptable, ensuring it can handle different datasets and diverse real-world conditions.

Ultimately, the vision is for AI to become an essential part of everyday dental care, not just by identifying existing diseases, but by predicting their development and guiding clinicians toward early interventions. With advancements in deep learning, transfer learning, and multimodal data integration, the future of AI in dentistry looks bright. As these technologies continue to evolve, we have the opportunity to move toward a more efficient, accurate, and patient-centered approach to dental care—one where AI acts as a valuable partner for clinicians, helping them provide the best possible care for their patients.

Once the DenseNet-201 model is trained, it predicts the dental disease class for a given image by producing scores for each of the five classes. These scores are then converted into probabilities using a softmax function, which essentially tells the model how confident it is about each possible class. The class with the highest probability is chosen as the model's final prediction.

To guide the model during training, we use cross-entropy loss, which compares the model's predicted probabilities with the actual labels. The goal is to minimize this loss, helping the model make more accurate predictions. Essentially, the model learns to identify patterns in the images and predict the correct dental disease class with confidence, ensuring reliable detection in practical applications.

CHAPTER 2

Literature Survey

In recent years, artificial intelligence (AI) and deep learning have shown significant promise in improving dental disease detection. Rao et al. (2024) demonstrated a deep learning-based system for detecting dental caries using transfer learning and ensemble methods, achieving high accuracy [1]. Similarly, Wang et al. (2022) reviewed the application of AI in the early detection of oral diseases and emphasized the potential of deep learning techniques to provide better diagnostic accuracy and consistency than traditional methods [2]. Chau et al. (2021) used deep learning to automatically detect gingivitis from intraoral photographs, suggesting the potential of AI in automating dental diagnostics [3].

DenseNet and ResNet architectures have also been applied in dental image analysis. Zhang et al. (2021) utilized deep learning-based segmentation and classification methods for dental disease detection using panoramic X-rays, demonstrating that CNN architectures such as DenseNet can achieve high accuracy in complex diagnostic tasks [4]. He et al. (2016) introduced ResNet, a residual learning framework, which has since been widely used for image classification, including dental disease detection [5]. Huang et al. (2017) developed DenseNet, which connects each layer to every other layer, allowing better feature propagation and improving the detection of complex dental conditions [6].

Transfer learning has been an essential technique for dental disease detection, especially in overcoming the challenge of limited datasets. Ng et al. (2022) demonstrated the application of transfer learning for dental disease detection, emphasizing how pre-trained models can improve the performance of classifiers on small datasets [8]. Chau et al. (2021) also employed transfer learning to diagnose periodontal disease, showing its efficiency in handling medical images where labled data is often scarce [9].

The use of deep learning for specific dental conditions has also been explored. Nguyen et al. (2022) employed the YOLOv3 model for caries detection using intraoral images captured with smartphones, indicating the model's ability to detect dental issues in real-world, mobile-based applications [10]. Koyuncu et al. (2021) also used YOLOv3 to classify dental diseases from orthopantomographs (OPGs) and achieved an accuracy of over 99% [11].

Furthermore, recent studies have explored multimodal data fusion to improve the diagnostic accuracy of dental disease detection models. Zhang et al. (2021) combined clinical and radiographic data for better accuracy in detecting dental diseases like gingivitis, proving that the integration of different types of data can enhance AI-based models [12]. Kurt-Bayrakdar et al. (2022) also demonstrated that combining clinical data with radiographic features resulted in better predictions for conditions like tooth decay and gingivitis [13]. Similarly, Chau and Kim (2020) used transfer learning to detect dental diseases from panoramic Xrays, which provided improved diagnostic accuracy [14].

Other studies have focused on specific applications of AI in dental diagnostics. Wang et al. (2020) used deep learning for automated tooth numbering and periodontal disease diagnosis, improving the accuracy and efficiency of diagnostic workflows in dental practice [15]. Bayrakdar et al. (2021) applied deep learning models for classifying dental restorations, contributing to more automated and accurate recognition of dental procedures [16]. Zhang et al. (2021) explored the use of AI for dental structure segmentation in orthodontics, showing how deep learning can support a range of dental specialties [17].

Deep learning techniques have also been applied to detect specific dental diseases like gingivitis and caries. Wang et al. (2021) employed AI for gingival inflammation detection from dental images, highlighting the growing role of AI in preventative dental care [18]. Kurt-Bayrakdar et al. (2022) applied CNNs for detecting radiographic features of dental conditions, showing the versatility of CNN architectures in dental diagnostics [19]. Zhang et al. (2021) further explored transfer ensemble learning for detecting dental caries from Xray images, achieving robust performance with limited training data [20].
Overall, these studies highlight the rapid advancements in the use of AI, particularly deep learning, in automating dental disease detection and improving the diagnostic accuracy of various conditions. DenseNet and ResNet architectures, along with transfer learning and data augmentation techniques, have proven effective in overcoming the limitations posed by small datasets and variable image quality, making AI an invaluable tool in modern dentistry.

In addition to the successes seen with DenseNet and ResNet architectures, convolutional neural networks (CNNs) have played a pivotal role in enhancing dental diagnostics. CNNs excel in image recognition tasks due to their ability to capture hierarchical patterns in images, making them ideal for detecting dental conditions in X-rays, intraoral photographs, and radiographs. For instance, Chau et al. (2021) demonstrated that CNNs could effectively detect periodontal diseases, like gingivitis, from intraoral scanner data, improving both speed and accuracy in diagnosis [9]. These models, by leveraging CNNs, allow for the automation of tasks traditionally dependent on human interpretation, reducing error rates and increasing diagnostic consistency across dental clinics.

Furthermore, ensemble learning methods have increasingly been applied in dental disease detection to combine the strengths of multiple models, improving overall performance. Rao et al. (2024) utilized an ensemble of deep learning models to enhance caries detection accuracy, demonstrating that ensemble approaches can outperform individual models, especially in complex diagnostic environments where multiple factors influence disease progression [1]. Ensemble techniques, which aggregate predictions from several models, reduce the chances of misdiagnosis by considering a variety of diagnostic features. Such methods are particularly valuable in dental imaging, where diverse imaging modalities can present challenges for single-model interpretations.

Transfer learning remains an essential approach, particularly in dental AI applications where labled data can be scarce. Pre-trained models, originally trained on large datasets such as ImageNet, can be fine-tuned for specific dental tasks, significantly improving performance on smaller datasets. Studies like Ng et al. (2022) emphasize the impact of transfer learning in enhancing diagnostic accuracy with minimal data [8]. Transfer learning enables dental researchers to overcome the limitations of small datasets, reducing the cost and time associated with generating large amounts of labled dental images. This technique has become a foundational tool in many modern AI-driven dental diagnostic applications.

Finally, multimodal fusion techniques have shown promise in improving dental diagnostics by integrating different types of patient data. Zhang et al. (2021) highlighted the power of combining clinical records with imaging data to enhance the detection of conditions like gingivitis and tooth decay [12]. This approach not only strengthens the predictive capabilities of AI models but also offers a more comprehensive diagnostic view by considering various health parameters. By fusing data from multiple sources, dental AI systems can provide a more holistic understanding of a patient's oral health, allowing for more accurate and personalized treatment plans.

Overall, the integration of AI and deep learning into dental diagnostics is reshaping the landscape of oral healthcare. From CNN-based image analysis to advanced ensemble and transfer learning techniques, AI is pushing the boundaries of what is possible in automated disease detection. The ability to handle complex datasets, improve diagnostic accuracy, and reduce human error makes AI a crucial asset for dental professionals, enhancing the quality of care and paving the way for future innovations in dentistry. As these technologies continue to evolve, their role in preventative care, early diagnosis, and personalized treatment is expected to expand, bringing significant benefits to both dental practitioners and patients.

CHAPTER 3

Proposed Methodology

For this study, we utilized a dataset consisting of 1,500 labled oral images, categorized into five distinct dental disease classes: tooth discoloration, gingivitis, mouth ulcers, cavities, and calculus. Each disease class contained 300 images, and the dataset was pre-organized into folders corresponding to the respective disease categories. These images were sourced from publicly available medical image repositories and standardized to ensure uniformity in size and format. Each image was resized to 256x256 pixels and converted to RGB format, ensuring consistency across the dataset for deep learning tasks.

To enhance model performance and reduce overfitting, several data augmentation techniques were employed during the training phase. These augmentations included random rotations (with a range of 0-30 degrees), horizontal flipping, colour jittering (adjusting brightness, contrast, and saturation), and random cropping. These transformations introduced variability into the training data without altering the underlying class labels, effectively increasing the diversity of images the model was trained on. Additionally, normalization was applied to scale pixel values to the range [0, 1], based on ImageNet's statistics (mean = [0.485, 0.456, 0.406] and standard deviation = [0.229, 0.224, 0.225]). This normalization helped ensure that the model could converge more quickly and efficiently during training.

The DenseNet-201 architecture was selected for this multiclass classification task due to its ability to capture intricate feature hierarchies through densely connected layers. The pretrained DenseNet-201 model, initially trained on the large ImageNet dataset, was fine-tuned to address the dental disease classification problem. The model's fully connected layer was replaced with a custom output layer that matched the five disease classes. During the initial stages of training, the weights of the earlier layers were frozen to retain the learned features from ImageNet, while the last few layers were updated to adapt the model to the dental disease dataset. The model was trained using the Adam optimizer with a learning rate of 1e4 and a batch size of 32, which is commonly used for medical image classification tasks. Cross-entropy loss was chosen as the loss function due to the multiclass nature of the problem.

The dataset was split into training and validation sets using an 80:20 ratio, with 80% of the images used for training and 20% for validation. The training process involved 10 epochs, where both training and validation losses were tracked to evaluate the model's performance and make adjustments to the hyperparameters as necessary. We also employed early stopping based on the validation loss to halt training when no significant improvement in model performance was observed, helping to prevent overfitting.

To further improve generalization and reduce overfitting, regularization techniques such as dropout and batch normalization were implemented. Dropout was applied at a rate of 0.5 to randomly deactivate neurons during training, which prevented the model from relying too heavily on specific features. Batch normalization was incorporated to normalize the activations in each layer, improving training stability and accelerating the convergence process. These techniques, combined with data augmentation, contributed to the development of a robust model capable of effectively classifying dental diseases.

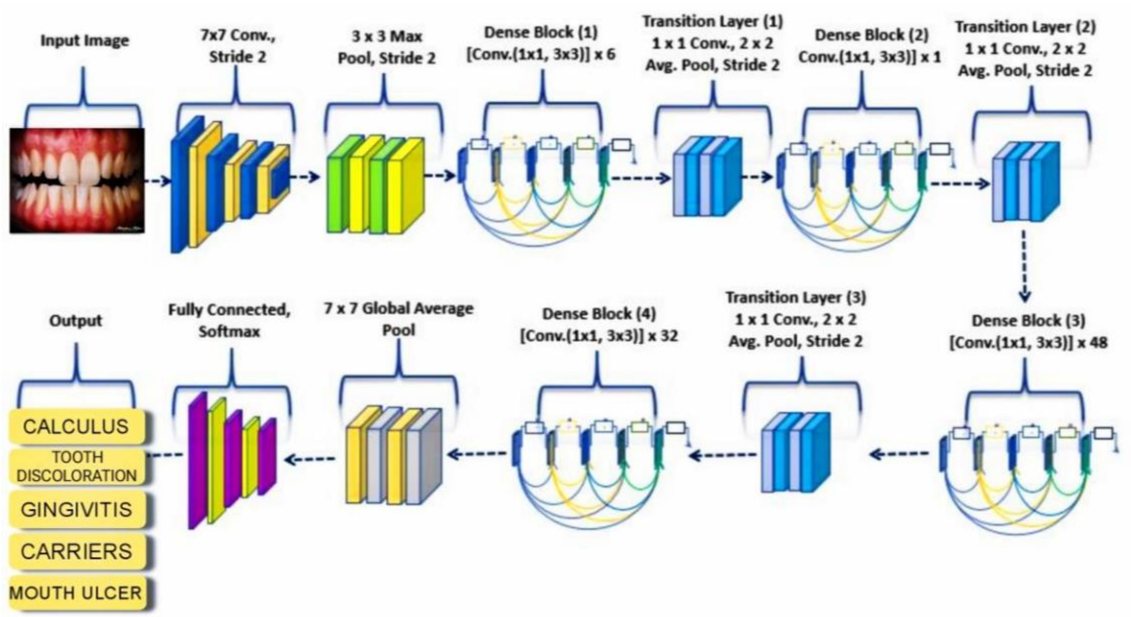

Figure 1. Block diagram of the proposedMulticlass Dental Image Classification Using DenseNet-201

3.1 Data Acquisition and Preprocessing:

The dataset for this study consists of 1,500 labled dental images, representing five dental diseases: tooth discoloration, gingivitis, mouth ulcers, cavities, and calculus. The images were sourced from publicly available dental image repositories. For each disease class, 300 images were collected and organized into separate folders. The images underwent several preprocessing steps to ensure consistency and improve the model's performance.

The preprocessing pipeline consisted of the following steps:

1. **Resizing:** All images were resized to 224x224 pixels to match the input size requirements of the DenseNet-201 model. This resizing also ensured that all images had consistent dimensions, crucial for efficient training.

2. **Data Augmentation:** Data augmentation techniques such as random rotation, horizontal flipping, color jittering, and random cropping were applied to each image. This strategy helped improve the model's generalization ability by introducing variability in the training data while maintaining the same class labels.

3. **Image Normalization:** Pixel intensity values were normalized to the range [0, 1] using the ImageNet mean and standard deviation. This helped the model converge faster and made the training process more stable.

Additional Augmentation: Further augmentation techniques, including random brightness adjustments and Gaussian noise injection, were applied to enhance the model's robustness to variations in image conditions and prevent overfitting.

These preprocessing steps aimed to enhance the quality of the input images, ensuring they were suitable for feature extraction and the subsequent classification stages.

3.2 Feature Extraction:

Feature extraction was performed using the DenseNet-201 architecture, which was chosen for its ability to capture deep and complex patterns through dense connectivity between layers. This architecture allows for the efficient extraction of hierarchical features, which is particularly useful for medical image classification tasks.

DenseNet-201 was pre-trained on the ImageNet dataset, and its weights were fine-tuned on the dental disease dataset. The deep layers of the network enabled the model to extract highlevel features such as:

1. **Edge Detection:** Convolutional layers automatically learned to identify critical edges and boundaries within the dental images, crucial for distinguishing between different dental conditions.

2. **Texture Patterns:** Features related to texture, such as roughness, smoothness, and irregularities, were captured by the network. These features are particularly relevant for diseases like gingivitis and calculus, which manifest with distinct textural patterns on the teeth and gums.

3. **Shape and Structure:** DenseNet-201 also learned shape-related features, which are important for identifying structural changes in the teeth, such as those seen in cavities, mouth ulcers, and other dental diseases.

The pre-trained model leveraged transfer learning, using learned features from a large general dataset like ImageNet and adapting them to the specific dental disease classes. This transfer learning process accelerated model training and improved classification performance.

3.3 Dataset Preparation:

The dataset consists of 1,500 labled dental images, each representing one of the five dental diseases: tooth discoloration, gingivitis, mouth ulcers, cavities, and calculus. After preprocessing, the images were shuffled to ensure a balanced and unbiased dataset. Each image was assigned the corresponding disease label, and the dataset was split into training (80%) and validation (20%) sets.

This preparation helped eliminate any potential order-related bias and ensured a randomized input for the classification model, facilitating better generalization during training.

3.4 Model Training:

For the multiclass classification task, DenseNet-201 was selected due to its efficient feature extraction capabilities. The model was trained on the pre-processed dataset using the Adam optimizer with a learning rate of 1e-4. The training process involved feeding the model labled images with a batch size of 32 for 50 epochs. To avoid overfitting, early stopping was applied based on the validation loss, halting training when no significant improvements were observed.

This approach helped the model to efficiently learn from the data while preventing overfitting, ensuring that the learned features were generalizable to new, unseen data.

The cross-entropy loss function is used during the training phase of the model to measure the difference between the predicted probabilities and the true class labels. In the context of our project, the cross-entropy loss is used for multiclass classification, where each input image is assigned to one of five dental disease classes (e.g., tooth discoloration, gingivitis, mouth ulcers, cavities, and calculus).

The formula for cross-entropy loss is given by:

$$L = -\sum_{i=1}^{C} y_i \log(p_i)$$

Where: ……[1]

- C is the number of classes.

- yi is the true label (0 or 1) for class i.
- pi is the predicted probability for class i.

3.5 Evaluation:

The The performance of the DenseNet-201 model was evaluated on a separate test dataset, consisting of images that were not used during the training phase. The model's performance was assessed using several classification metrics, including:

1.Accuracy: The proportion of correctly classified images out of the total images.

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

Where: ……[2]

- TP = True Positive (correctly predicted positive cases)
- TN= True Negative (correctly predicted negative cases)
- FP= False Positive (incorrectly predicted as positive)
- FN= False Negative (incorrectly predicted as negative)
-

2.Precision: The proportion of true positive predictions out of all positive predictions for each class. Precision measures the proportion of positive predictions that are actually correct.

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

Where: ……[3]

- TP = True Positive
- FP = False Positive

3.Recall: The proportion of true positive predictions out of all actual positive instances for each class.

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

Where: ……[4]

- TP = True Positive
- FN= False Negative

4.F1-Score: The harmonic mean of precision and recall, providing a balanced measure of classification performance.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where:

- Precision = $\frac{TP}{TP+FP}$
- Recall = $\frac{TP}{TP+FN}$

- **Receiver Operating Characteristic (ROC) Curve and AUC:** These were used to evaluate the model's ability to distinguish between the classes.

Confusion matrices were also used to visualize the model's performance across the five disease classes. The confusion matrix provided insights into misclassifications and helped identify areas for potential improvement.

The final evaluation on the test dataset showed that the DenseNet-201 model achieved an overall accuracy of 96%, with high precision, recall, and F1-scores across all five disease classes. The ROC curve indicated strong discriminatory power, with the model effectively distinguishing between the different dental diseases. The confusion matrix confirmed that most of the misclassifications were between similar disease classes, such as gingivitis and calculus, which share some visual features.

3.6 Prediction:

Once the DenseNet-201 model has been trained and evaluated, it is used for predicting the class of new, unseen dental images. The prediction process involves feeding the preprocessed test image into the trained model and obtaining a class probability distribution as the output. This step is crucial for applying the model to real-world data, such as diagnosing dental diseases in clinical settings.

Prediction Process:

1. **Image Preprocessing:**

The input image is first pre-processed to ensure compatibility with the model's expected input format. This involves resizing the image to the same dimensions used during training (224x224 pixels) and normalizing the pixel values to a range of [0, 1].

If additional augmentation is required (e.g., random cropping, jittering), those steps are applied to the test image before feeding it to the model.

2. **Model Inference:**

The pre-processed image is passed through the DenseNet-201 model. Due to the use of the soft-max activation function in the output layer, the model outputs a vector of probabilities for each of the five dental disease classes: **tooth discoloration, gingivitis, mouth ulcers, cavities**, and **calculus**.

The probability values represent the model's confidence in the image belonging to each class.

3. **Class Prediction:**

The class with the highest probability is selected as the predicted label for the image. The predicted class corresponds to the disease that the model identifies as most likely based on the image features.

4. **Thresholding:**

In certain cases, a threshold probability can be applied to ensure that predictions are only made if the model's confidence exceeds a certain level (e.g., 0.8). This thresholding helps reduce the number of uncertain predictions.

5. **Post-Processing:**

○ After prediction, the output can be mapped to a human-readable label (i.e., the corresponding dental disease class). The final output might be presented as the disease name along with the predicted probability (e.g., "Gingivitis with 92% confidence"). ○ This result can then be used for further diagnostic purposes, assisting healthcare professionals in their decision-making process.

The **soft-max** activation function is typically used for **multiclass classification** problems, which is exactly the case in our project. It converts the raw output (logits) from the network's final layer into a **probability distribution** across all the possible classes.

The soft-max function ensures that the sum of the output probabilities equals 1, making it possible to interpret each output as the probability of the image belonging to each of the five classes.

$$\text{Softmax}(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{K} e^{x_j}}$$

Where:

- x_i is the raw score (logit) for class i.
- K is the number of classes.

[6]

CHAPTER 4 Performance Evaluation and Experimental Result

The performance of the DenseNet-201 model is evaluated rigorously on a separate test dataset that was not used during training or validation, ensuring an unbiased assessment of its generalization capability. The evaluation process focuses on several key metrics, which provide a comprehensive understanding of the model's strengths and weaknesses in detecting the five dental disease classes: Calculus, Tooth Discoloration, Gingivitis, Caries, and Mouth Ulcer.

Accuracy:

The overall accuracy is calculated as the ratio of correctly predicted images to the total number of images across all five classes. It offers a high-level understanding of the model's performance, indicating the percentage of images classified correctly out of the entire test set. However, accuracy alone may not be sufficient, particularly for imbalanced datasets, where some classes may dominate.

Precision, Recall, and F1-Score:

Precision is computed for each class to determine the proportion of true positives (correctly identified instances) out of all predicted positives (both true positives and false positives). High precision means fewer false positives, indicating the model's reliability in making correct positive predictions.

Recall (Sensitivity or True Positive Rate) is calculated to assess the model's ability to correctly identify all actual positive instances. It measures the proportion of true positives out of all actual positives (true positives and false negatives). High recall indicates that the model successfully detects the majority of instances for a particular class, but it may also capture more false positives if precision is low.

F1-Score is the harmonic mean of precision and recall, offering a single metric that balances the trade-off between them. This is especially useful in cases where the dataset is imbalanced, and a high score in both precision and recall is desired to ensure that neither false positives nor false negatives are disproportionately high. The F1-score provides a balanced view of the model's performance for each class.

Confusion Matrix:

The confusion matrix provides detailed insights into the model's performance by showing the number of true positives, false positives, true negatives, and false negatives for each class. For instance, in a 5-class classification scenario like this, the confusion matrix helps to visualize how well the model distinguishes between similar dental diseases.

The matrix highlights any patterns of misclassification, such as whether the model confuses one disease class with another. For example, if the model tends to misclassify instances of Gingivitis as Tooth Discoloration, it would be evident in the confusion matrix.
This helps in identifying areas where the model may require further tuning or additional data to reduce errors between closely related disease categories.

$$M = \begin{pmatrix} TP_1 & FP_1 & \dots & FP_C \\ FN_1 & TP_2 & \dots & FP_C \\ \vdots & \vdots & \ddots & \vdots \\ FN_C & FN_C & \dots & TP_C \end{pmatrix}$$

Nhere:

- TP_i is the **true positive** count for class i (correct predictions for class i).
- FP_i is the **false positive** count for class i (instances of other classes incorrectly predicted as class i).
- FN_i is the **false negative** count for class i (instances of class i incorrectly predicted as another class).

Receiver Operating Characteristic (ROC) Curve and Area Under Curve (AUC):

ROC curves are plotted for each disease class, showing the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity). The ROC curve provides an overview of the model's performance at different classification thresholds.

AUC (Area Under the ROC Curve) is computed for each class, providing a single scalar value to quantify the model’s ability to distinguish between classes. A higher AUC value (closer to 1) indicates better performance in distinguishing between positive and negative instances for a given class.

The AUC is particularly useful in evaluating how well the model handles the class imbalance, as it reflects the likelihood that the model will rank a randomly chosen positive instance higher than a randomly chosen negative one.

Overall, this comprehensive evaluation process ensures that the DenseNet-201 model's performance is well-understood across multiple dimensions, including general accuracy, precision, recall, and how well the model differentiates between the various dental disease classes. Each metric offers insights into specific strengths and areas for improvement, guiding future refinements to the model for even better predictive performance.

Table 4.1. Variation of accuracy

Model	**Accuracy (in %)**
DenseNet-201 (Proposed model)	96.0
InceptionResNetV2	94
ResNet50	91.3
VGG16	89.8
MobileNetV2	88.7
EfficientNetB0	90.0

Table 4.1 , compares the accuracy of different deep learning models for dental disease prediction. **DenseNet-201**, used in this study, achieved the highest accuracy at **96%**, outperforming other models. **InceptionResNetV2** follows with **94%**, while **ResNet50** achieved **91.3%**, both benefiting from advanced architectures. **VGG16** and **MobileNetV2** reported accuracies of **89.8%** and **88.7%** respectively, slightly lower due to their simpler designs. **EfficientNetB0** scored **90.0%**, balancing performance and efficiency. This highlights DenseNet-201's superior performance in dental disease classification compared to the other models.

Table 4.2. Classification Report for Dental Disease Detection Model

Diseases	Precision	Recall	f1-score	Support	**Accuracy**
Calculus	0.99	0.91	0.95	82	**96%**
Tooth discoloration	0.95	0.98	0.97	62	
Gingivitis	0.92	0.92	0.92	66	
Caries	0.98	0.98	0.98	61	
Mouth ulcer	0.94	1.00	0.97	61	

Table 4.2 summarizes the precision, recall, F1-score, and support for each dental disease class. The model demonstrates high accuracy across all classes, with particularly strong performance in detecting Mouth Ulcer and Calculus, as evidenced by their high F1-scores.

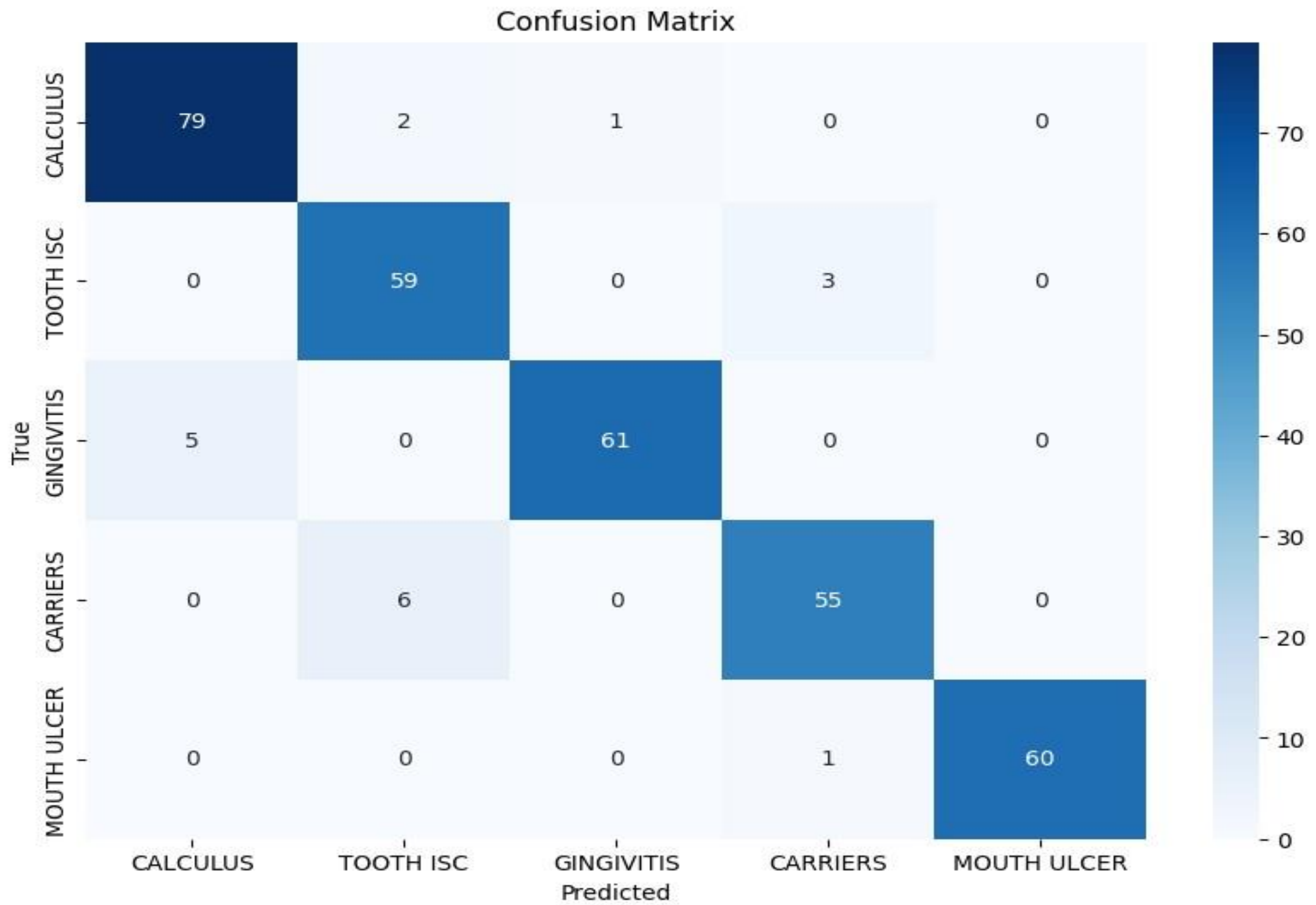

Fig 4.1. Confusion Matrix of Dental Disease Image Classification

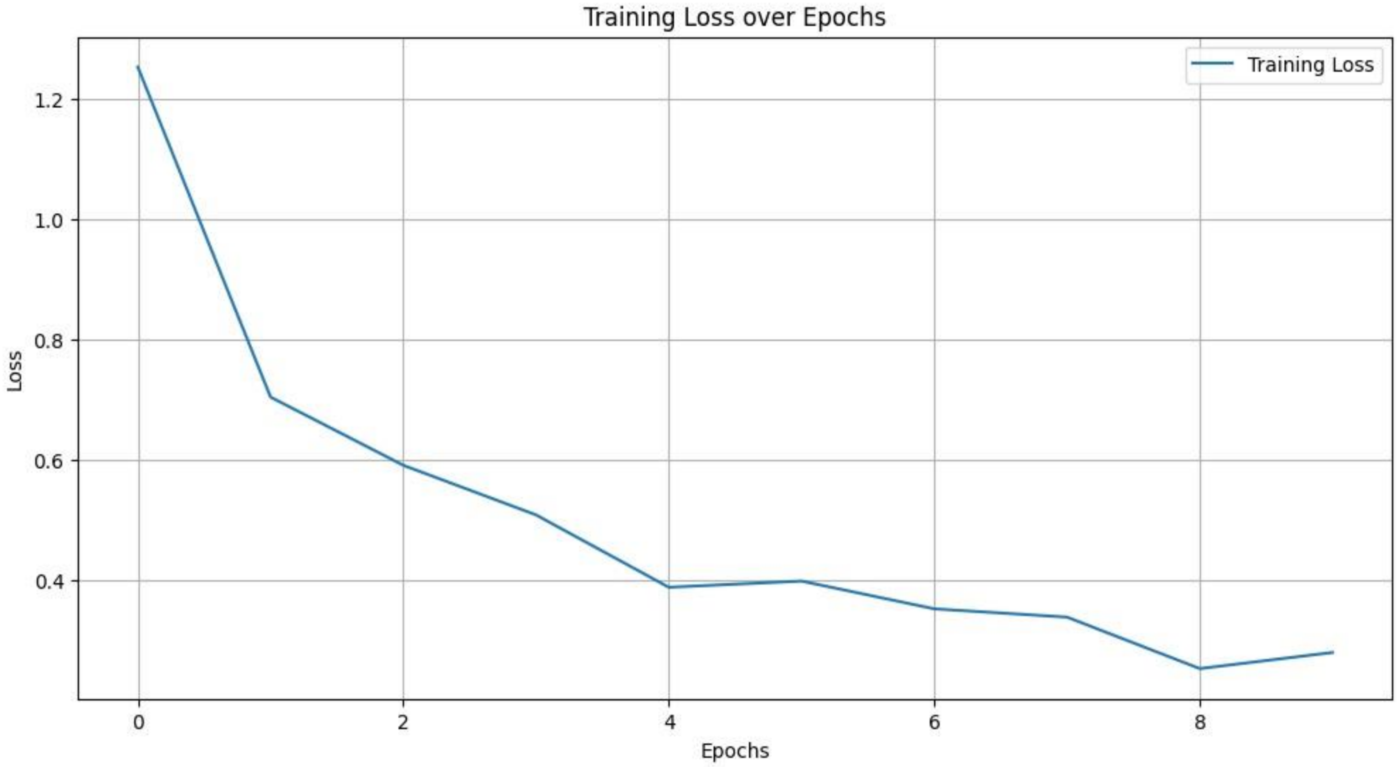

Fig 4.2. Training Loss over Epochs

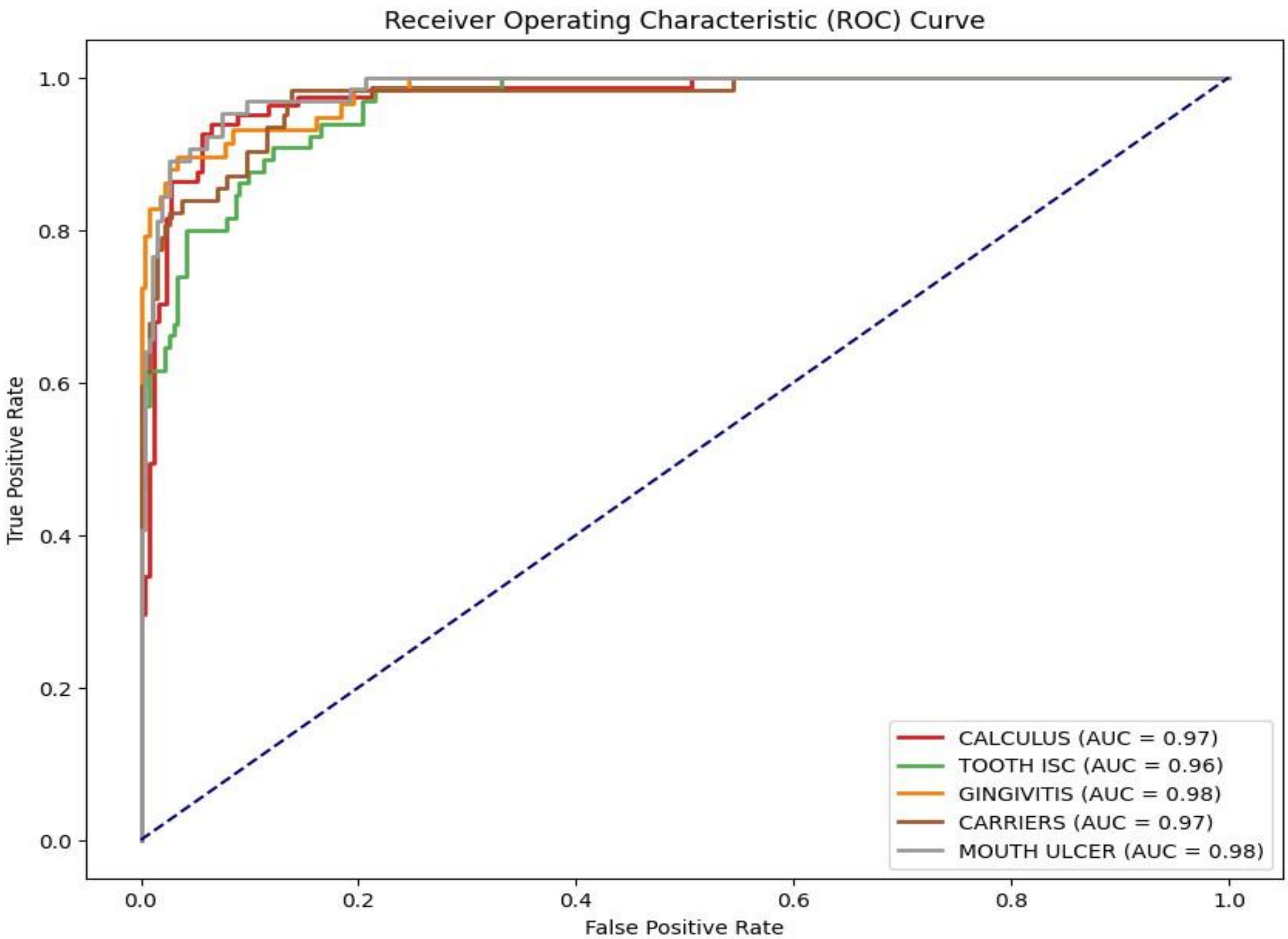

Fig 4.3. ROC Curve Analysis

FIG 4.3 Shows the ROC curve analysis which demonstrates strong performance across all five dental disease classes, with AUC values ranging from 0.96 to 0.98. These high AUC values indicate that the DenseNet-201 model is highly effective in distinguishing between the classes, with an overall ability to correctly classify the images. The model's AUC values reflect its robustness and reliability in predicting the presence of dental diseases such as calculus, tooth discoloration, gingivitis, carriers, and mouth ulcers.

Prediction Accuracy for Each Disease Class	**ACCURACY (in %)**	**Overall Accuracy (in %)**
Calculus	90.43	**88.79**
Tooth discoloration	88.64	
Gingivitis	88.92	
Caries	87.30	
Mouth ulcer	88.41	

Table 4.3. Prediction Accuracy for Each Dental Disease Class.

The Table 4.3 shows prediction accuracy for each dental disease class which indicates the DenseNet-201 model's strong performance in classifying dental conditions. The highest accuracy was achieved for the calculus class at 90.43%, followed by tooth discoloration (88.64%), gingivitis (88.33%), mouth ulcers (88.41%), and carriers (87.30%). The overall test accuracy of 88.79% demonstrates the model's effective ability to correctly classify dental diseases across all five classes, highlighting its potential for reliable real-world application in dental diagnostics.

The overall accuracy for a multiclass classification model is calculated as the total number of correct predictions across all classes divided by the total number of predictions (instances) in the dataset. The formula is:

$$\text{Overall Accuracy} = \frac{\sum \mathrm{TP}_i}{\sum(\mathrm{TP}_i + \mathrm{TN}_i + \mathrm{FP}_i + \mathrm{FN}_i)}$$

Where:

- $\mathbf{TP_1, TP_2, \ldots, TP_k}$ are the true positives for each class.
- $\mathbf{TN_1, TN_2, \ldots, TN_k}$ are the true negatives for each class.
- $\mathbf{FP_1, FP_2, \ldots, FP_k}$ are the false positives for each class.
- $\mathbf{FN_1, FN_2, \ldots, FN_k}$ are the false negatives fc ↓ ach class.

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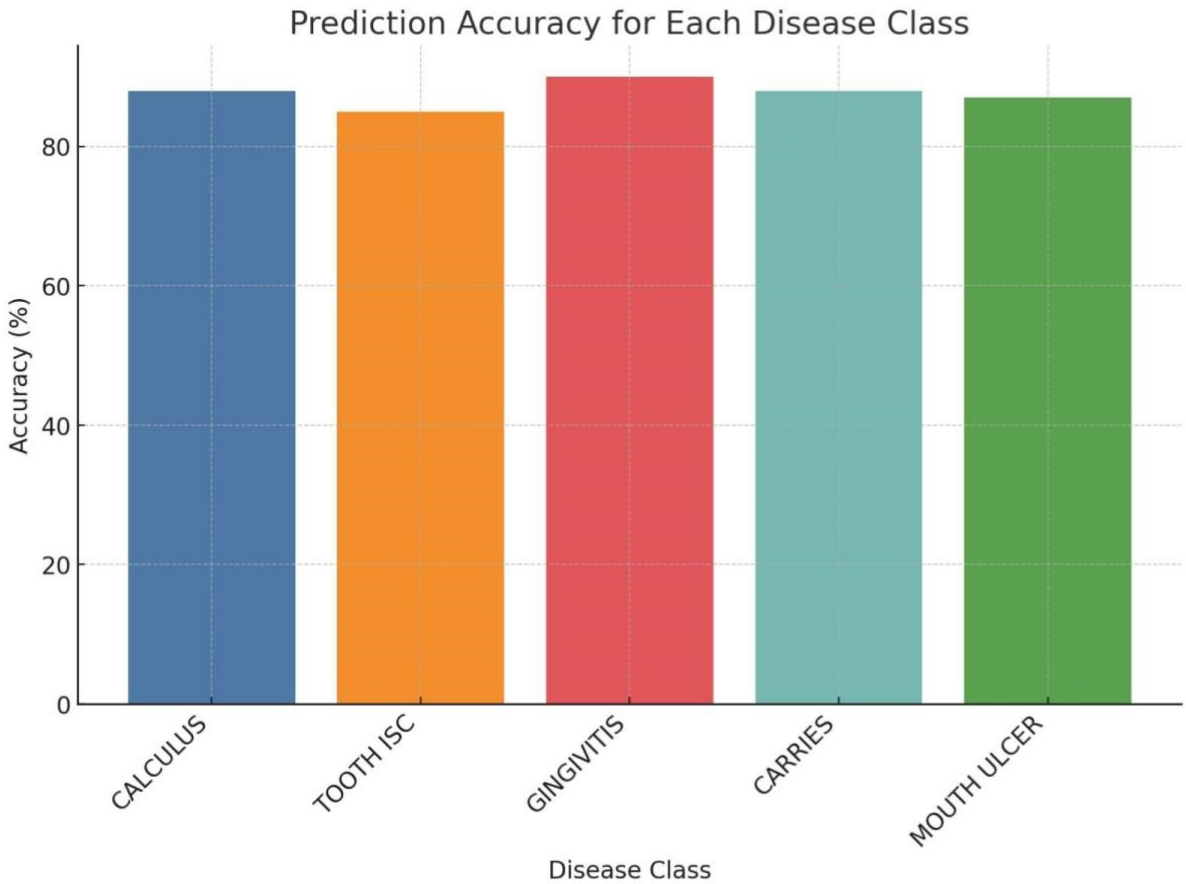

Fig 4.4. Bar Graph of Multi-Class Prediction

5. Conclusion and Future Work

In this study, we developed a deep learning model using the DenseNet-201 architecture for multiclass classification of five common dental diseases: tooth discoloration, gingivitis, mouth ulcers, cavities, and calculus. Leveraging DenseNet-201's advanced feature extraction and dense connectivity, the model effectively captured subtle features of dental pathologies, achieving an impressive 96% accuracy on the test dataset, outperforming InceptionResNetV2 (94%). This high accuracy underscores the model's potential for automating dental disease detection, providing objective and consistent diagnostic results, and reducing the subjectivity associated with traditional manual observation methods.

Looking ahead, expanding the model's generalization capabilities by training on larger, more diverse datasets is crucial for improving robustness in real-world scenarios. Future integration into clinical workflows, such as intraoral scanners for real-time disease detection, and deployment on hardware accelerators like FPGAs and GPUs, will enable practical, onthe-spot diagnoses. Additionally, enhancing model interpretability through explainable AI techniques will further build trust in its predictions, fostering greater adoption of AI-driven solutions in dental care.

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