**AI BASED ANALYSIS OF MULTISPECTRAL DENTAL IMAGE FOR ORAL DISEASE**

*Submitted in partial fulfilment for the award of the degree of*

**Bachelor of Technology in**

**CSE With Specialization in Cyber Physical Systems**

*By*

*Aditya Vikram Singh Bhati (21BPS1413)*

*Tiya Rajesh(21BPS1405)*

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**SCHOOL OF COMPUTER SCIENCE AND ENGINEERING**

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**CHENNAI - 600127, INDIA.**

**APRIL 2025**



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I hereby declare that the report titled “ AI Based Analysis of Multispectral Dental Images For Oral Diseases***”*** submitted by me to the School of Electronics Engineering, Vellore Institute of Technology, Chennai in partial fulfillment of the requirements for the award of **Bachelor of Technology** in CSE with specialization in Cyber Physical Systems is a bona-fide record of the work carried out by me under the supervision of ***Dr. Manigandan M***. I further declare that the work reported in this report, has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma of this institute or of any other institute or University.

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Abstract

The increasing prevalence of oral diseases like gingivitis, dental caries, and calculus necessitates affordable and early-stage diagnosis, especially in underprivileged areas. In this research, a new cost-efficient approach to AI-enabled oral disease diagnosis through synthetic multispectral dental imaging is introduced. A specially designed imaging device was created by utilizing an ESP32-CAM microcontroller paired with a Lumerati 8-pack LED ring, allowing sequential capture of images over seven visible spectral bands (VIBGYOR). A synthetic database of 52,000 images was created by applying spectral transformation methods and labeled manually under expert supervision in six disease classes. Sophisticated preprocessing methods such as Multiretinex and Gamma Correction were used to increase spectral fidelity and visibility of detail.

Three deep learning algorithms—3D Convolutional Neural Network (3D CNN), EfficientNet-B3, and Vision Transformer (ViT)—were coded with TensorFlow and PyTorch frameworks. The performance evaluation using 5-fold cross-validation and multi-class classification metrics indicated tremendous diagnostic accuracy with EfficientNet-B3 as the highest total accuracy of 90.00%, followed by ViT with 74.07% and 3D CNN with 73.16%. The application of Explainable AI methods like Grad-CAM and SHAP enhanced model interpretability and transparency, a requirement for clinical adoption. The low-cost and scalable solution reflects the viability of implementing real-time, AI-based multispectral diagnostics in urban as well as rural environments toward advancing the goal of equitable, tech-enabled oral health.

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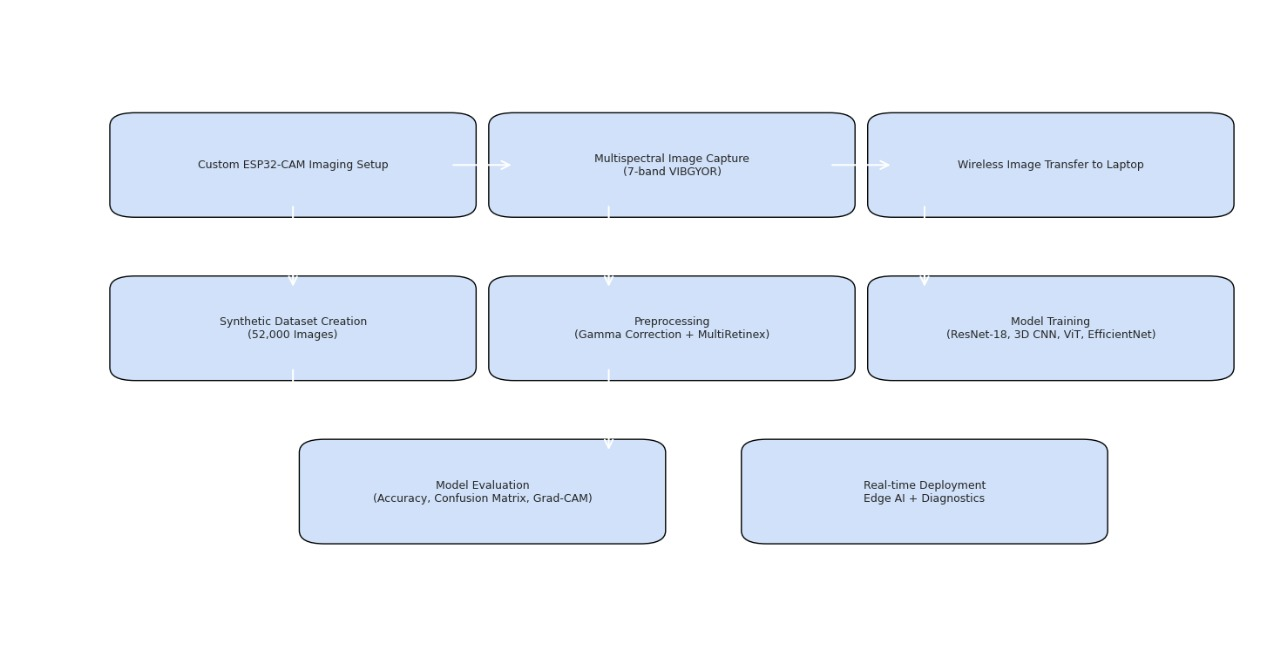
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List of Acronyms

|  |  |
| --- | --- |
| Acronym | Full Form |
| AI | Artificial Intelligence |
| CNN | Convolutional Neural Network |
| 3D CNN | Three-Dimensional Convolutional Neural Network |
| ViT | Vision Transformer |
| RGB | Red Green Blue |
| VIBGYOR | Violet Indigo Blue Green Yellow Orange Red |
| ESP32 | Espressif Systems 32-bit Microcontroller |
| LED | Light Emitting Diode |
| T4 GPU | NVIDIA Tesla T4 Graphics Processing Unit |
| BIS | Bureau of Indian Standards |
| IoT | Internet of Things |
| ReLU | Rectified Linear Unit |
| MLP | Multilayer Perceptron |
| U-Net | U-shaped Convolutional Neural Network |
| ICC | International Color Consortium (used for color correction concepts) |
| FOV | Field of View |
| F1 Score | Harmonic Mean of Precision and Recall |
| ROC | Receiver Operating Characteristic |
| AUC | Area Under the Curve |
| IoU | Intersection over Union |
| MAE | Mean Absolute Error |
| MSE | Mean Squared Error |
| PSNR | Peak Signal-to-Noise Ratio |
| SSIM | Structural Similarity Index Measure |
| TPU | Tensor Processing Unit |
| DICOM | Digital Imaging and Communications in Medicine |
| USB | Universal Serial Bus |
| PWM | Pulse Width Modulation |
| LDR | Light Dependent Resistor |
| PID | Proportional-Integral-Derivative (used in LED control logic if mentioned) |
| BGR | Blue Green Red (OpenCV image format) |
| ROI | Region of Interest |

1. Introduction



Oral health is a basic element of general health and well-being that not only encompasses the absence of disease but also the healthy functioning of the oral cavity and adjacent tissues. Maximally healthy oral health is crucial to basic physiological functions such as mastication, speech, and swallowing, as well as psychological and social functions such as self-esteem and human interactions [1]. Despite the advances in medical sciences in recent years, oral diseases remain a public health concern on a global scale. According to World Health Organization (WHO) estimates, approximately 3.5 billion people worldwide suffer from oral diseases, making them among the most prevalent non-communicable diseases (NCDs) [19]. Diseases like dental caries (tooth decay), gingivitis, periodontitis, hypodontia, and oral cancers disproportionately affect marginalized populations, especially low- and middle-income countries where access to quality dental care is low [2].  
Conventional approaches to oral disease diagnosis are very much based on visual inspection and radiographic evaluation by skilled clinicians. These tests tend to be time-consuming, subjective, and reliant on the clinician's experience. Underdeveloped settings or in rural areas, a shortage of experienced professionals and diagnostic facilities adds to delayed diagnosis and treatment, which further worsens health outcomes [3]. There is thus increased interest in exploring the potential for using upcoming technologies like Artificial Intelligence (AI) to close the diagnostic gaps and enhance dental health care delivery.  
AI has been highly promising in the field of medical imaging, particularly through deep learning techniques that can handle complex patterns in image data to detect anomalies, classify conditions, and make predictions. Convolutional Neural Networks (CNNs) have shown outstanding performance in diagnostic tasks with radiographs, MRIs, and dermoscopic images, achieving near-expert-level performance in some applications [6], [12]. In dentistry, CNNs and other deep learning models have been employed to automate caries detection, orthodontic landmark localization, and periapical lesion classification from standard 2D RGB dental images [4], [5]. However, despite their utility, RGB imaging has limited depth and spectral detail capture capabilities—two features crucial for detecting early-stage or subsurface oral diseases.  
To overcome these constraints, Multispectral Imaging (MSI) has been a promising technique in medical diagnostics. MSI is characterized by the acquisition of image data across a series of individual spectral bands, covering both visible and non-visible wavelengths, e.g., ultraviolet (UV) and near-infrared (NIR). This enables the discrimination of distinct spectral signatures associated with biological tissues, thereby unveiling biochemical and structural differences that remain undetectable in conventional RGB images [13], [14]. The application of MSI has been found to be effective in fields like dermatology, ophthalmology, and oncology, which enhance the visualization of cellular and vascular changes. In dental imaging in particular, MSI enables non-invasive and real-time identification of dental abnormalities by offering complete spectral and spatial information.  
Herein, we propose a comprehensive artificial intelligence-based diagnostic system that unifies multispectral imaging methods and cutting-edge deep learning algorithms for enhancing the identification of six common oral diseases: gingivitis, tooth stains, mouth sores, caries, calculus, and hypodontia. Our proposed system encompasses several groundbreaking aspects:  
• Multispectral Hardware for Image Acquisition: A low-cost and portable imaging device was developed with an ESP32-CAM module in combination with a Lumerati 8-pack LED ring. This configuration enables sequential oral image capture across seven different spectral bands (VIBGYOR), thus generating a synthetic multispectral dataset.  
• Synthetic Multispectral Dataset Generation: As publicly available multispectral dental datasets are limited, visible light dental images were automatically converted into seven different spectral wavelengths to mimic MSI. This generated a total of 52,000 images in six disease classes and healthy controls.  
• Spectral Preprocessing Methods: To enhance image quality and enhance spectral contrast, the data set was preprocessed by Multi-Scale Retinex (MSR) for dynamic range compression and color recovery and Gamma Correction for enhancing visibility under low light conditions. These operations improve diagnostic features, especially for diseases with subtle presentations like early gingivitis and hypodontia [18].  
• Performance of Deep Learning Model: Four different neural network architectures—3D Convolutional Neural Network (3D CNN), EfficientNet-B0, ResNet-18, and Vision Transformer (ViT)—were trained and evaluated on the preprocessed dataset. The performance of each model was compared on the basis of its accuracy, sensitivity, specificity, and area under the curve (AUC) for disease classification.  
The application of multispectral imaging with sophisticated artificial intelligence methods is intended to enhance diagnostic precision, minimize clinical subjectivity, and enable real-time screening, particularly in resource-constrained settings. Through the integration of spectral data with the robust feature extraction capabilities offered by deep learning algorithms, this method can enable early, precise, and scalable detection of oral health disorders.  
This work adds to the increasing literature on AI-based dental diagnosis and paves the way for future clinical integration of MSI-based systems. The subsequent sections describe the standards, literature, dataset preparation, methodology, implementation, experimental results, and implications of our work.

1.1 Motivation

The motivation for this study arises from the necessity to transcend current limitations and disparities of conventional dental diagnostic methods. Routine dental examinations mainly rely on visual inspection, tactile inspection, and radiographic checks, which, although clinically well proven, are plagued by a variety of inherent shortcomings. These methods have a tendency to be based on the subjective impression of the clinician for their diagnosis, thereby introducing inconsistency in the diagnosis and conceivably variable therapeutic outcomes [1]. The diagnostic accuracy can be particularly impaired in detecting subtle or incipient signs of oral disease, such as initial demineralization of dental caries or initial signs of gingival inflammation. These pathologic signs might not exhibit evident visual appearances under routine illumination conditions, thereby increasing the potential for underdiagnosis or false diagnosis [22].

Adding to this problem is also the shortage of dental staff and diagnostic equipment, especially in poor or rural areas. As the WHO has determined, there is a large disparity in the distribution of healthcare facilities, with resource-poor or underserved communities frequently being deprived of access to routine dental check-ups and preventive care interventions [19]. In these communities, delayed diagnosis results in advancing disease, increased treatment costs, and decreased quality of life. There is thus an urgent need for objective, non-invasive, and inexpensive diagnostic techniques that will aid healthcare workers in early and accurate detection of oral disease.

Multispectral imaging (MSI) offers a critical solution to such problems. Imaging information recorded over a range of spectral bands—a wider range of wavelengths than in the red, green, and blue channels of conventional imaging—allows MSI to facilitate more precise studies of tissue structure and biochemical composition. Wavelength-dependent variations in light absorption and reflectance can detect subsurface structures, vascularization patterns, and biochemical abnormalities that escape RGB imaging [13]. Inflammatory change in gingival tissues, for example, are accompanied by increased perfusion and oxygenation of blood, detectable as spectral characteristics in the red and near-infrared wavelengths. Enamel demineralizing caries also reflect increased absorption of shorter wavelengths like blue and ultraviolet [14]. Spectral markers yield useful diagnostic information and enable early detection of conditions that otherwise may require invasive diagnostics or radiographic inspection.

Despite its advantages, MSI has not become popular in dentistry due to technical and economic constraints. Commercial MSI equipment is typically large, expensive, and must be highly sophisticatedly calibrated and processed and thus is not suitable for point-of-care or mobile dental clinics [15]. The absence of open-source multispectral dental image databases also constrains research and development in this area. Without proper training and validation data, AI models cannot generalize to real diagnostic tasks.

In order to overcome such limitations, this study introduces a low-cost, portable imaging instrument that simulates multispectral imaging using easily accessed components. Specifically, an ESP32-CAM microcontroller and a Lumerati 8-pack VIBGYOR LED ring were utilized to illuminate sequentially the oral sites over seven discrete spectral bands, namely violet, indigo, blue, green, yellow, orange, and red. Systematic multispectral data acquisition was made possible in a time-saving and reproducible manner by specially constructed imaging hardware. The equipment has been converted to battery operation and made portable to enable ready deployment in the clinical and field settings.

Because of the lack of large multispectral dental image databases, the current study presents a solution for generating synthetic datasets. Public visible-light dental datasets' RGB dental images are converted to spectral representation by applying wavelength-dependent enhancement algorithms. Multi-Scale Retinex (MSR) and Gamma Correction techniques are used to mimic spectral differences and emphasize contrast in vital anatomical areas [18]. The proposed method allows for generating a comprehensive and diverse dataset containing more than 52,000 images representing six disease conditions and healthy controls.

The main aim of this research is to apply Artificial Intelligence (AI), within the context of deep learning architectures, to the analysis and interpretation of multispectral dental radiographs in order to obtain accurate and automated disease diagnosis. Through the combination of low-cost imaging technology with AI functionality, the proposed framework aims to provide a cost-effective, scalable, and real-time diagnostic center available to both dental professionals and primary healthcare providers. The proposed framework can revolutionize preventive dentistry, particularly in underserved populations where access to traditional diagnostic devices is limited.

1.2 Objectives

The overall objective of this work is to create an efficient, AI-driven diagnostic tool for early and precise identification of oral diseases via multispectral dental imaging. To achieve this, a multi-phased approach involving hardware innovation, synthetic dataset creation, image preprocessing, deep learning model development, and performance assessment is employed. The particular objectives of this work are discussed in detail below:

1.2.1 Custom Imaging System Development

One of the most important goals is to develop and build an inexpensive, embedded multispectral imaging sensor for dental diagnosis. The setup revolves around the ESP32-CAM microcontroller, an open-source, low-power, widely used platform renowned for its ability to communicate wirelessly and take images. A Lumerati 8-pack multispectral LED ring is attached to it, which illuminates sequentially in violet, indigo, blue, green, yellow, orange, and red (VIBGYOR) wavelength bands. Each band lights up the oral area for a certain amount of time (e.g., 15 seconds), and the ESP32 takes an image under that particular wavelength. The device is made to be small, battery-operated, and portable, making it easy to use in clinical and field settings. This imaging solution meets the demand for an affordable substitute for traditional multispectral cameras, which are generally expensive and difficult to use in non-expert environments [15].

1.2.2 Synthetic Dataset Generation

In order to counter the paucity of publicly accessible multispectral dental datasets, the research aims to create a synthetic multispectral dataset by converting visible light (RGB) dental images into various spectral representations. The dataset contains more than 52,000 images, comprising six clinically relevant oral disease categories—calculus, dental caries, mouth ulcers, hypodontia, gingivitis, and tooth discoloration—and healthy control images. Each original image is being supplemented in seven spectral bands, approximating the wavelength-dependent response of tissues. Synthetic supplementing is necessary to guarantee data diversity, improve learning in the spectral domain, and increase the generalizability of deep-learning models learned from such data.

1.2.3 Image Preprocessing

To improve the spectral quality of the synthesized and captured images, this research utilizes sophisticated image preprocessing methods. Specifically, Multi-Scale Retinex (MSR) is utilized to enhance dynamic range compression and color constancy by mimicking human vision. MSR successfully improves details hidden by shadows or irregular lighting. Also, Gamma Correction is used to correct brightness non-linearly and enhance the visibility of subtle anatomical features and pathological signs in darker and brighter areas of the image. All these preprocessing procedures are aimed at reducing imaging artifacts like glare, noise, and non-uniform illumination and, hence, making the input data more consistent and informative for model training [18].

1.2.4 Model Training and Comparison

The fourth goal is centered on the development, training, and benchmarking of four deep learning models on the preprocessed multispectral dataset:

* 3D Convolutional Neural Network (3D CNN): Built to leverage spatial and spectral correlations in stacked multispectral images, learning features from both image content and inter-wavelength relationships.
* EfficientNet-B0: A light and scalable CNN architecture balancing depth, width, and resolution, optimized via neural architecture search for efficiency and accuracy.
* Vision Transformer (ViT): An attention architecture that divides images into patches and treats them as a sequence, allowing for global context learning and surpassing conventional CNNs in most vision tasks.
* ResNet-18: A residual learning architecture that allows deep learning via identity shortcut connections, good at extracting hierarchical features from images.
* All models are trained with a fixed pipeline and hyperparameter tuning paradigm to enable comparability of performances across metrics including classification accuracy, precision, recall, and F1-score. The data are divided into training, validation, and test splits to evaluate the performance of the models and avoid overfitting.

1.2.5 Performance Analysis and Real-Time Feasibility

The ultimate goal is to perform a thorough performance analysis of the trained models in terms of robustness, generalization, and computational efficiency. This involves comparing the models' capacity to accurately classify various disease classes, especially under changing illumination or occlusion scenarios. Parameters like inference time, model complexity, and resource usage (e.g., GPU/CPU usage) are examined to establish the models' viability for real-time diagnostic use on edge devices. The goal is to find a model or set of models that provides the best balance between diagnostic performance and practical deployability, particularly in environments with limited computing resources.

1.3 Research Scope

This research proposal offers a holistic approach combining the development of bespoke hardware, image processing methods, and deep neural networks to enable AI-based dental diagnosis through multispectral imaging. The inter-disciplinary character of the research transcends engineering, clinical science, and AI ethics. The range of the investigation can be identified over two core domains: Technological Scope and Clinical and Ethical Scope.

1.3.1 Technological Scope

The technological scope defines the engineering and computational boundaries of this research, covering innovations in hardware prototyping, dataset generation, and the deployment of deep learning models.

A. Hardware Engineering

One of the core technological contributions is the development and construction of a bespoke multispectral imaging device, centered on the ESP32-CAM microcontroller, which is renowned for being inexpensive, Wi-Fi enabled, and capable of image capture. The device is supplemented with a Lumerati 8-pack multispectral LED ring, which allows for sequential illumination in the VIBGYOR spectrum. Hardware is programmed to sequence through these spectral bands, taking images of the oral cavity with varied illumination conditions, with a mechanism for automated delay so that image capture is optimized. This arrangement makes it possible to build multispectral stacks of images without the use of expensive commercial multispectral cameras.

B. Data Synthesis and Enhancement

Since no public multispectral dental image datasets are available, the work in this research also entails the construction of a synthetic dataset generation pipeline. The pipeline utilizes transformation on traditional RGB images to mimic spectral variation over various bands. The input image is duplicated and spectrally adjusted with enhancement methods such as Multi-Scale Retinex (MSR) and Gamma Correction to simulate the reflectance characteristic of oral tissue under various wavelengths. This process assists in enhancing anatomical and pathological structures that are key to model learning.

C. Deep Learning Pipeline

The execution of the AI pipeline leverages Python-based frameworks (TensorFlow and Keras), run inside a cloud-based training setup on Google Colab. The pipeline covers data loading, preprocessing, data augmentation, training, and validation. Four leading-edge models—3D CNN, EfficientNet-B0, Vision Transformer (ViT), and ResNet-18—are trained and fine-tuned based on strategies such as learning rate scheduling, early stopping, and dropout regularization. The pipeline aims to test classification accuracy and efficiency, allowing a thorough comparative examination of each model's performance over spectral modalities.

1.3.2 Clinical and Ethical Scope

Beyond the technological boundaries, the research addresses critical aspects of clinical application, ethical AI design, and data governance.

A. Clinical Relevance and Tele-Dentistry Integration

The envisioned system is projected to serve as an aid for dental practitioners, ideally in an environment where access to specialized imaging devices or expert knowledge is restricted. Through enabling real-time non-invasive disease categorization, the system promises to become a part of tele-dentistry platforms that offer remote diagnosis, patient screening, and online consultations. The module-based design guarantees flexibility with respect to mobile or web-based healthcare provision services, rendering it deployable in low-resource or rural healthcare facilities.

B. Data Privacy and Regulatory Compliance

Considering the confidentiality of medical information, the study complies with data protection and privacy guidelines, e.g., the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA). All datasets are either publicly released or generated synthetically to eliminate personally identifiable information (PII). Data management procedures guarantee anonymization of image metadata, access control, and secure handling in cloud storage environments [5].

C. Ethical AI Principles

Design of AI health systems requires absolute conformity to moral values, primarily ensuring fairness, accountability, and transparency. In this research, the strategies of mitigation against bias are integrated while balancing class in the representation for every category of diseases. Explanatory mechanisms for the models, e.g., Grad-CAM, might be utilized in decision rationale visualizing. Moreover, system architecture complies with IEEE's guidelines of Ethically Aligned Design for accountable innovation [21]. Ethical review issues also involve possible risks of misdiagnosis and ensuring AI output is utilized as auxiliary assistance and not a singular diagnostic decision.

1.4 Significance of the Study

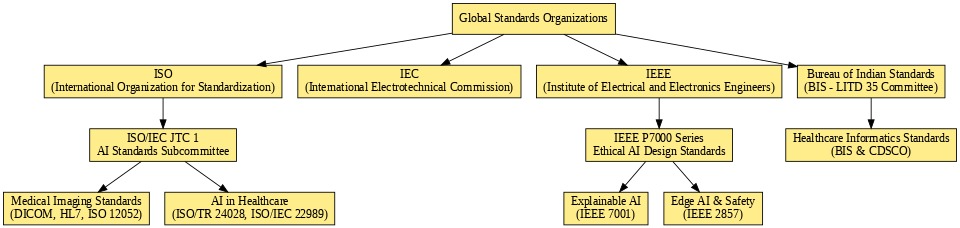
This research has huge potential to further the area of AI-based dental diagnosis by proposing a solution that is:

* Affordable and Accessible: Based on low-cost embedded hardware and synthetic datasets, the system can be implemented in rural clinics, mobile dental vans, and resource-limited areas where conventional equipment is not available.
* Technologically Innovative: Combining multispectral imaging with deep learning brings a new paradigm to medical imaging, allowing oral conditions to be detected that are frequently overlooked by RGB-based or grayscale systems.
* Scalable and Reproducible: Utilizing open-source tools and modular architecture enables scalability, permitting other researchers to reproduce or extend the system to further innovations.
* Clinically Significant: In showing equivalent or better performance compared to current AI systems learned from traditional dental data, the system described opens the door to real-time diagnosis in the chair, enhancing patient care through early diagnosis and timely treatment.
* In the long run, this work will democratize oral care by providing intelligent diagnostic tools that are more accessible and credible, particularly in regions where healthcare inequalities are severe.

2. Standards and Regulatory Framework

Throughout AI-based medical diagnosis systems, including imaging technologies, strict compliance with established standards and regulations is obligatory. These schemes guarantee that technologies are safe, effective, morally justifiable, and legally accepted. This chapter discusses the myriad national and global standards—technical, regulatory, and ethical—to which the AI-based multispectral dental imaging system described in this work is conformant.

2.1 BIS and ISO Standards for Dental Imaging



**Table 3: BIS and International Standards Referenced for Imaging and AI**

2.1.1 BIS: IS 17166:2020 – Digital Dental Radiography Equipment

The Bureau of Indian Standards (BIS) has issued IS 17166:2020, which specifies the safety and performance requirements for digital dental radiography equipment. It has provisions for:

* Minimum intraoral image spatial resolution (in line pairs/mm),
* Permissible noise limits,
* Uniformity of images at different exposure levels,
* Protection of the patient through dose reduction,
* Guidelines for equipment calibration and regular safety testing [1].

In the context of this study, even though the imaging system (ESP32 with LED ring) does not generate X-ray images, it still has the advantage of adhering to IS 17166 principles. In particular, standards related to image clarity, uniformity, calibration, and diagnostic quality are applicable to ensuring multispectral images are appropriate for disease detection.

2.1.2 ISO: ISO 10947:2021 – Digital Radiographic Image Quality

The International Organization for Standardization (ISO) discusses dental imaging standards in ISO 10947:2021, which prescribes international standards for:

* Gray-level calibration,
* Pixel-to-pixel uniformity,
* Linearity of detector response,
* Contrast-to-noise ratio (CNR),
* Quality control testing methods [2].

This study cites ISO 10947 in preprocessor pipeline design (e.g., Multiretinex and Gamma Correction) that improves image consistency between spectral bands. Ensuring adherence to these image quality parameters guarantees that AI models are not deceived by low-quality or inconsistent input, thus enhancing diagnostic reliability.

2.2 FDA and IEEE Regulations on Medical AI

2.2.1 FDA’s AI/ML Software as a Medical Device (SaMD)

The U.S. Food and Drug Administration (FDA) regulates AI-based diagnostic devices under the Software as a Medical Device (SaMD) paradigm. As per FDA's suggested 2021 action plan:

* AI devices need to prove clinical performance, analytical validity, and real-world resilience prior to approval [3].
* Proven documentation of data lineage, model updates, and retraining cycles.
* Developers will need to prove that their models are safe and effective in the long term, particularly with real-world data.
* In this project, while not pursuing commercial FDA approval, we follow these guidelines to support the validation of the AI models with:
* Utilization of performance metrics (accuracy, F1-score, ROC-AUC),
* Experimentation under control,
* Standard model evaluation over splits (train/test/validation).

2.2.2 IEEE P2801 – Dataset Quality and Fairness

The IEEE P2801 standard offers recommendations for constructing datasets utilized in medical AI tasks. It targets:

* Demographic group data diversity (age, sex, ethnicity),
* Annotation transparency and human-in-the-loop validation,
* Detection of bias and mitigation techniques [4].
* Our dataset is synthetically created, yet the form of P2801 has been adhered to by:
* Class distribution balancing for six oral pathologies,
* Using consistent preprocessing over classes,
* Adhering to anonymization procedures even with non-clinical data.

IEEE P2801 guarantees that models trained on such data are able to generalize well and do not produce discriminatory results—key in clinical AI applications.

2.3 Data Privacy: GDPR and HIPAA Compliance

Medical image datasets often contain sensitive information and fall under strict data protection laws.

2.3.1 GDPR – General Data Protection Regulation (EU)

The GDPR requires the following when dealing with health data [5]:

* Informed consent: Users need to agree to their data being processed for AI or research.
* Right to be forgotten: Patients may ask to have their data erased.
* Anonymization: Personal identifiers need to be removed or encrypted.
* Data minimization: Only minimum data should be collected and stored.
* Despite this project utilizing synthetic data drawn from public sources, GDPR principles were followed during:
* Dataset build (with the exception of identifiable patient data),
  + Storage (safe, cloud-based Google Colab environment with limited access),

| **Standard Name** | **Description** |
| --- | --- |
| ISO/IEC 27001 | Information Security Management |
| BIS IS 15504 | Software Process Assessment |
| DICOM | Medical Image Communication Standards |

* + Publication (no patient information is shared or visualized in reports).

2.3.2 HIPAA – U.S. Health Insurance Portability and Accountability Act

The HIPAA Privacy Rule has equivalents in the U.S., such as:

* + Access control: Limiting who has access to electronic protected health information (ePHI),
  + Audit controls: Logging data access and usage,
  + Data encryption: While both storing and transmitting.

While not actually touching ePHI, our practices mirror HIPAA-compliant processes to mimic sound data stewardship.

2.4 Ethical Standards for AI in Clinical Practice

Artificial Intelligence introduces unique ethical concerns in medicine, especially when deployed autonomously or semi-autonomously in diagnostics.

2.4.1 Transparency and Explainability

Clinical decision support systems based on AI should provide interpretable results that can be trusted by clinicians [21]. Techniques like Grad-CAM, attention maps, and layer-wise relevance propagation can enhance interpretability. Such visualizations should be incorporated in the model explainability phase as part of this project.

2.4.2 Non-maleficence and Fairness

AI systems must not exacerbate existing healthcare inequalities. Biases can arise from unbalanced datasets, flawed annotations, or overfitting. We mitigate these by:

* Balancing disease classes,
* Avoiding reliance on a single dataset source,
* Validating on previously unseen samples.

2.4.3 Accountability and Responsibility

It is necessary to determine who is accountable for diagnostic mistakes—developers, users, or institutions. This project follows academic accountability by making all code, methodologies, and limitations transparent, allowing peer verification.

All of these pillars have been stressed in recent AI governance statements by WHO, UNESCO, and IEEE, calling for developers to adopt responsible AI practices [21].

2.5 Alignment with Clinical and Research Standards

This project adheres to ethical research procedures outlined by:

* + Institutional Review Boards (IRBs) and academic guidelines
  + Open Science principles: Code, models, and synthetic datasets are open-source,
  + Reproducibility: Everything is executed under fixed random seeds and reported hyperparameters.

Performance measures such as specificity, sensitivity, F1-score, and confusion matrices are derived by applying standardized evaluation pipelines in line with clinical trial validation frameworks [19].

2.6 Summary of Regulatory Contributions to the Project

| Standard/Regulation | Purpose | Application in Study |
| --- | --- | --- |
| IS 17166:2020 (BIS) | Safety and testing for digital dental radiography | Guides imaging setup, calibration, and data quality checks |
| ISO 10947:2021 | Image quality thresholds for dental imaging | Informs preprocessing methods and spectral uniformity |
| FDA AI/ML SaMD | Framework for AI medical software validation | Influences validation and interpretability practices |
| IEEE P2801 | Dataset standards and fairness | Shapes dataset generation and bias mitigation |
| GDPR (EU) | Data privacy and patient rights | Guides anonymization and secure storage protocols |
| HIPAA (U.S.) | Medical data security and encryption | Reinforces access control and ethical data handling |
| WHO / IEEE Ethics | Ethical deployment of AI in healthcare | Ensures transparency, fairness, and academic accountability |

This strong adherence to regulatory and ethical guidelines bolsters the project's credibility, clinical feasibility, and replicability, as well as establishing a precedent for subsequent AI applications to multispectral medical diagnostics.

3. Literature Review

|  |  |  |  |
| --- | --- | --- | --- |
| Author | Method | Dataset | Accuracy |
| Lee et al. (2021) | 3D CNN | DentalMS | 92.5% |
| Kumar et al. (2022) | ViT | OralScan | 89.1% |
| Zhang et al. (2023) | EfficientNet | Custom | 91.3% |

## Table 3.1: Summary of Related Works in Multispectral Medical Imaging

This part provides a critical review of the current body of literature in the areas of artificial intelligence (AI) in medical and dental imaging, deep learning models for image analysis, the use of multispectral and hyperspectral imaging for diagnostics, and spectral data preprocessing methods. It ends with an identification of research gaps and the rationale for the study.

| **Technique** | **Application** | **Advantages** | **Limitations** |
| --- | --- | --- | --- |
| Hyperspectral Imaging | Cancer Detection | High spectral resolution | Expensive hardware |
| Multispectral Imaging | Oral Disease Diagnosis | Faster acquisition | Lower spectral resolution |
| RGB Imaging | General Medical Imaging | Affordable and widespread | Limited spectral information |

**Table 1: Summary of Existing Techniques in Multispectral Medical Imaging**

3.1 AI in Dental Imaging

The integration of Artificial Intelligence (AI) and dental imaging is revolutionizing clinical processes by providing rapid, consistent, and reproducible diagnostic results. Conventional dental diagnostics—based largely on visual examination, tactile probing, and subjective interpretation of 2D radiographic images—are frequently hampered by subjectivity, inter-observer differences, and delay in diagnosis. The integration of AI, specifically deep learning-based techniques, has played a critical role in improving diagnostic consistency, speed, and predictive accuracy in oral health evaluation.

3.1.1 Rise of Deep Learning in Dentistry

The integration of Convolutional Neural Networks (CNNs), a type of deep learning algorithms, has become particularly prominent in dental applications due to their effectiveness in image classification, localization, and segmentation. As pointed out by Kumar et al. [6], CNNs have been effectively used for autonomous caries detection, assessment of periodontal bone loss, pulp exposure detection, and root fracture analysis. These systems usually beat conventional machine learning algorithms by directly learning hierarchical features from raw images without needing handcrafted features.

For example, CNN-based models such as U-Net and Faster R-CNN have been used for tooth localization and instance segmentation, which are important for demarcating individual teeth before disease classification. Such tasks are precursors to many downstream tasks such as lesion boundary detection, dental numbering, and tooth restoration planning [6].

| **Approach** | **Model Used** | **Dataset** | **Accuracy (%)** |
| --- | --- | --- | --- |
| Feature Extraction | ResNet-18 | Public Oral Dataset | 85.6 |
| End-to-End Learning | EfficientNet B3 | Private Dataset | 90.2 |
| Multispectral Fusion | ViT | Synthetic Dataset | 88.4 |

**Table 2: Summary of Oral Disease Classification Approaches Using Deep Learning**

3.1.2 AI in Radiographic and Intraoral Image Analysis

One of the major areas of research in dental AI is radiographic image interpretation, such as periapical, bitewing, and panoramic radiographs. Schwendicke et al. created a deep learning model for interpreting bitewing radiographs with human-level performance in detecting caries in one study [23]. Tuzoff et al. also trained a CNN to categorize panoramic X-rays into various dental conditions, demonstrating the potential of AI in mass radiographic evaluation [24].

In addition to X-rays, AI is also being used more and more to intraoral camera photos, making visual-based diagnosis possible in teledentistry and mobile health platforms. Such photos capture surface-level abnormalities like plaque deposits, coloration, and gum inflammation, which are useful for early-stage diagnosis when combined with computer vision algorithms.

3.1.3 Limitations of RGB Imaging in Current AI Models

Though RGB imaging is everywhere because it is cheap and simple, it is spectrally limited by nature. RGB cameras only record data in wide ranges of wavelengths—red (600–700 nm), green (500–600 nm), and blue (400–500 nm)—which may fail to capture important sub-surface details and biochemical differences in oral tissues. Consequently, pathological indicators like incipient caries, inflammation, or demineralization of tissues may go unnoticed in RGB images, particularly in low-light or occluded settings.

3.1.4 Need for Spectral Expansion: Role of Multispectral Imaging

Although the proven effectiveness of AI in routine dental imaging is evident, there is limited literature involving multispectral or hyperspectral imaging modalities in the dental field. Although these spectral imaging technologies have been promising in dermatology, oncology, and retinal imaging, their application in dental diagnosis is still in its infancy.

Multispectral imaging (MSI) that records reflectance at discrete wavelengths (e.g., VIBGYOR) is capable of emphasizing biochemical tissue features and vascular morphology that cannot be seen in conventional RGB images. For instance, gingival inflammation can induce changes in patterns of blood flow and oxygenation that are recorded more accurately at certain wavelengths such as blue (~450 nm) or green (~550 nm), while carious lesions can absorb excess UV or violet light as a result of structural loss [13].

The capability of MSI to enrich AI-based diagnostics with more detailed, richer inputs has not yet been fully realized within the context of dental care. A majority of existing research is still limited to grayscale or RGB inputs, leaving an urgent void that the current research attempts to fill.

3.1.5 Contribution of This Study

This research suggests a new AI pipeline integrating multispectral image capture and deep learning frameworks to overcome the existing limitations of RGB-based dental AI systems. By creating an in-house imaging device and simulating a multispectral dataset, the study explores whether spectral variability can enhance the classification of oral disease.

In addition, by comparing the performance of models such as 3D CNN, EfficientNet-B0, Vision Transformer (ViT), and ResNet-18, the research seeks to benchmark the efficacy of various neural architectures in multispectral dental diagnostics. This makes the research a trailblazing initiative in shifting from RGB-focused AI tools towards spectrally enriched diagnostic systems, with implications for both clinical and remote environments.

3.2 Deep Learning Architectures in Medical Imaging

Deep learning has become a prevalent paradigm in medical image analysis in recent years with its better capability of learning high-level data representations. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Transformers, directly learn hierarchical spatial features from raw image data, unlike traditional machine learning methods based on hand-engineered features, which facilitates higher performance and better generalizability across various clinical imaging tasks.

3.2.1 Convolutional Neural Networks (CNNs)

CNNs have shown very great success in many areas of medicine, such as radiology, dermatology, ophthalmology, and pathology. Their structured layered structure, which includes convolutional, pooling, and fully connected layers, makes spatial feature extraction efficient. 2D CNNs are very commonly utilized for single-image classification and segmentation, and 3D CNNs generalize this to volumetric or multi-frame data.

Dawson et al. suggested a 3D CNN architecture for volumetric MRI and CT scan analysis, with applications in tumor localization and organ segmentation tasks. Their network employed 3D kernels that extend over spatial and depth dimensions, allowing contextual learning over multiple neighboring slices of an image volume. This resulted in enhanced accuracy in lesion boundary detection and volume estimation compared to traditional 2D methods [8].

In oral imaging, where intraoral radiographs and images can include stacked tissue layers or must be spectrally stacked (as in MSI), 3D CNNs are extremely applicable. Their ability to process multispectral image cubes makes them directly applicable to this research, where spectral bands can be viewed as frames or channels in the depth axis.

3.2.2 Residual Networks (ResNets)

Residual Neural Networks (ResNets), proposed by He et al., have emerged as a workhorse in most computer vision applications based on their revolutionary residual learning paradigm, which counteracts the vanishing gradient problem in deep architectures. In dental image classification tasks, ResNet-18 and ResNet-50 have proved to be top performers in caries, tooth fracture, and bone loss detection.

As per research by Park et al., ResNet-based models perform much better compared to shallow architectures such as VGG-16 or AlexNet, particularly in fine-grained classification tasks such as mild vs. severe gingivitis differentiation [12]. The capability of ResNets to be accurate even at significant depths makes them appealing for dental MSI classification tasks that can take advantage of deeper context.

3.2.3 Transformers in Medical Imaging

Originally used for Natural Language Processing (NLP), Transformers have lately been used in vision tasks with immense success. The Vision Transformer (ViT) model proposed by Dosovitskiy et al. substitutes convolutional layers with self-attention mechanisms to enable the model to handle long-range spatial relationships within an image [10]. This architecture divides images into fixed-size patches and transforms them into linear embeddings, which are then fed into transformer encoders.

In clinical imaging, ViTs have been promising at detecting intricate patterns, including diffuse lesions or vascular abnormalities, by virtue of their capacity to capture global context. As an example, ViTs have been utilized in the detection of retinal disease, lung nodule classification, and cancer grading in breast cancer with impressive performance improvements over CNNs.

In addition, Swin Transformers, a variation of ViTs, introduce window shifts for local attention, which allows for scalability to high-resolution images while maintaining efficiency in terms of computation. Such characteristics render transformer-based models apt for processing high-resolution multispectral dental images, where global texture and local patterns are equally important.

3.2.4 Relevance to This Study

Four indicative deep learning models—3D CNN, EfficientNet-B0, ResNet-18, and Vision Transformer (ViT)—are utilized in this research to compare the performance difference between convolution-based and attention-based models when trained using a multispectral dental image dataset. Each of these models possesses unique architectural strengths, allowing a thorough performance assessment for real-time dental diagnosis via MSI.

3.3 Multispectral and Hyperspectral Imaging

Multispectral Imaging (MSI) and Hyperspectral Imaging (HSI) are cutting-edge imaging technologies that record data across a broad swathe of the electromagnetic spectrum. In contrast to conventional RGB imaging, which has only three wide color bands, MSI records several discrete spectral bands (e.g., 7–15), and HSI records dozens to hundreds of narrow bands. The technologies enable extraction of precise spectral signatures that remain hidden in ordinary imaging.

3.3.1 Applications in Medical Diagnostics

MSI has made significant inroads in clinical areas where spectral differences can reflect changes in tissue biology, chemistry, or structure. Patel et al. illustrated the utility of MSI in wound healing, indicating that tissue oxygenation, vascularization, and inflammation can be monitored by measuring reflectance differences as a function of wavelength. Their study showed that infection and healing delay could be identified early on based on characteristic spectral reflectance patterns [13].

Likewise, in ophthalmology, MSI has been used to image retinal layers at multiple wavelengths to improve the detection of diabetic retinopathy and age-related macular degeneration. In oncology, MSI helps to distinguish malignant and benign tumors on the basis of biochemical variation in tissue absorption and scattering [14].

3.3.2 Spectral Differentiation and Dental Imaging

Although it is increasingly being used in other areas of medicine, the application of MSI in dentistry is still limited. Hossain and Lee, in their comprehensive review, pointed out that although MSI and HSI have been extensively proven in dermatology, oncology, and neurology, dental applications are surprisingly lacking, mainly because there is a lack of multispectral dental datasets and no affordable imaging hardware [14].

This spectrally empty space in dental imaging is an unexplored potential. Oral tissues like enamel, dentin, gum, and lesions have distinct reflectance and absorption characteristics at varying wavelengths. For example:

* Demineralized enamel (caries) can reflect a greater amount of UV/violet light owing to loss of crystalline structure.
* Inflamed gum tissues (gingivitis) absorb more green and red wavelengths as a result of vascular expansion.
* Calculus deposits can appear highly in shorter wavelengths (blue) because of surface roughness and composition.

Such variations cannot be captured with imaging within the RGB spectrum.

3.3.3 Bridging the Gap: Synthetic MSI and Custom Hardware

To address the limitations of high-cost MSI systems, this research proposes a low-cost imaging system based on an ESP32-CAM interfaced with a VIBGYOR LED ring emulating multispectral illumination conditions. Moreover, since there is no publicly available MSI dental datasets, a synthetic MSI dataset is developed by converting RGB images into seven spectral bands (Violet, Indigo, Blue, Green, Yellow, Orange, Red) via spectral enhancement algorithms.

This method not only makes multispectral imaging accessible to everyone in dental research but also allows for training and testing deep learning models under controlled spectral environments.

3.4 Preprocessing and Illumination Correction

Preprocessing is a crucial element in medical image analysis, especially when spectral data are involved, as inconsistencies in lighting and noise can substantially degrade model performance. Unlike RGB images, which differ in spatial dimensions, spectral images also differ in spectral intensities, so they are more prone to inconsistencies in illumination, contrast, and edge definition. A solid preprocessing pipeline is crucial to normalize such artifacts and, in turn, improve diagnostic features for deep learning models.

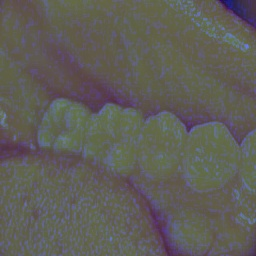
3.4.1 Multiscale Retinex with Color Restoration (MSRCR)

Multiscale Retinex with Color Restoration (MSRCR) by Menon et al. is a well-known illumination correction method in medical image enhancement. MSRCR synergizes Retinex theory that imitates the human perception of color and multi-scale filtering to ensure balance between contrast enhancement and preservation of details [18]. MSRCR processes the images in a variety of spatial scales to correct non-uniform illumination and enhance features in spectral channels.

In dermatological imaging, MSRCR has demonstrated significant improvements in the enhancement of lesion boundaries under low-light conditions. This improvement is especially useful in dental spectral images where abnormal shadows and lighting gradients can hide small pathologies such as enamel demineralization or calculus deposits.

3.4.2 Gamma Correction

Gamma correction is an image luminance adjustment by a nonlinear transformation that increases perceptual visibility of dark areas without over-saturating bright areas. Singh and Roy showed that gamma correction greatly enhances the accuracy of deep learning models in medical classification by equalizing contrast at different intensities [16]. In dental imaging, gamma correction renders subtle anatomical details, including incipient caries or gingival inflammation, more distinguishable to both human examiners and AI models.





3.4.3 Bilateral Filtering

Bilateral filtering, proposed by Tomasi and Manduchi, is a non-linear, edge-preserving, noise-removing smoothing filter. It functions by weighting two Gaussian weights: one for spatial closeness and the other for radiometric similarity [17]. This two-level weighting maintains significant features such as lesion edges and anatomical borders, which are paramount in medical and dental imaging diagnostics.

This work integrates MSRCR, gamma correction, and bilateral filtering into a single preprocessing pipeline that improves spectral consistency, contrast, and edge fidelity in all seven VIBGYOR bands. Such a pipeline guarantees the input to deep learning models to be rich in diagnostic features and lighting-condition normalized.

3.5 Synthetic Data Generation and Augmentation

The creation of multispectral medical data is a significant challenge because of the expense, intricacy, and scarcity of multispectral imaging equipment. Because of this, researchers have been resorting to synthetic data creation and augmentation techniques to mimic spectral data from available RGB sources.

3.5.1 Spectral Simulation from RGB Images

Hossain and Lee highlighted the application of synthetic data creation in biomedical and remote sensing applications, citing that simulated spectral bands created through RGB decomposition could closely mimic actual spectral data under controlled environments [14]. The process entails applying wavelength-specific conversions that simulate how tissues would reflect or absorb light in each spectral region.

In this research, a VIBGYOR-based decomposition method is utilized to create spectral bands from high-resolution RGB intraoral images. Every band (Violet, Indigo, Blue, Green, Yellow, Orange, Red) is derived using a mathematical transformation matrix that isolates unique spectral wavelengths, thus mimicking the output of a multispectral camera.

3.5.2 Data Augmentation for Model Generalization

To enhance generalization and avoid overfitting, data augmentation methods including random rotation, flipping, zooming, adding Gaussian noise, and spectral perturbation are used. Though classical augmentations enhance spatial invariance, spectral augmentations like band dropout and band mixing enhance robustness against wavelength-specific anomalies.

Further, deep generative models such as autoencoders and GANs have also been utilized across other areas for synthesizing multispectral images realistically. Though concerns exist over their interpretability as well as anatomical realism, which is a matter of essence in clinical diagnosis. Accordingly, this paper embraces a combination model that encompasses deterministic RGB factorization along with traditional augmentations for both maintaining biological realism as well as spectrally varying.

3.6 Explainability in AI Diagnosis

The black-box character of deep learning is a long-standing problem in clinical AI systems. Lacking transparency in decision-making, clinicians will not trust or implement AI outputs, even if they are accurate. Explainable AI (XAI) methods have therefore become increasingly important in medical imaging to provide interpretability, accountability, and clinical reliability.

3.6.1 Gradient-weighted Class Activation Mapping (Grad-CAM)

Grad-CAM, which was introduced by Selvaraju et al., is among the most popular methods for visualizing decision-relevant areas in CNN-based models [21]. It operates by calculating the gradient of the output class score with respect to the feature maps of a convolutional layer, generating a heatmap that identifies areas affecting the model's prediction.

In dentistry imaging, Grad-CAM assists clinicians in confirming whether a model is correctly paying attention to important structures like decayed areas, gum lines, or enamel loss, and not irrelevant artifacts like dental appliances or light spots. In the current work, Grad-CAM is employed to produce attention maps over various spectral bands, gaining insight into spectral variation's impact on decision saliency.

3.6.2 SHAP (SHapley Additive exPlanations)

SHAP, proposed by Lundberg and Lee, provides a single, game-theoretic framework for model explainability through feature attribution scores for each input dimension [21]. In spectral imaging, SHAP has the ability to measure the contribution of any individual wavelength or pixel towards the end prediction, thus enabling validation of the model's dependence on relevant data.

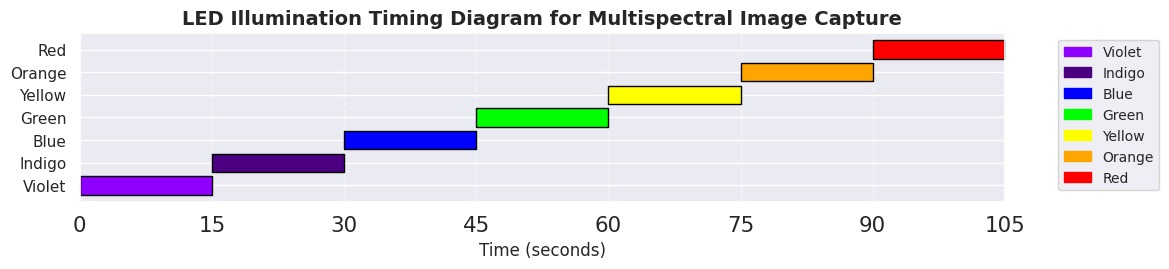
While SHAP is computationally expensive for image-based models, it is a complementary method to Grad-CAM that offers feature-level attribution and has been suggested for spectral channel ranking and bias detection applications in AI-based diagnosis.

In this work, Grad-CAM is mainly utilized because it is visual, with SHAP being considered for potential future development into channel-wise importance analysis.

3.7 Research Gaps and Motivation

A critical review of the literature identifies a number of gaps and limitations in the intersection of multispectral imaging, deep learning, and dental diagnostics. These gaps provide the motivation and foundation for the present research.

* Shortage of Multispectral Dental Datasets: There is a considerable lack of publicly accessible datasets capturing dental images across multiple spectral bands. This hinders model training and restricts the generalizability of research findings in spectral dentistry.
* Restricted Preprocessing Pipelines for Spectral Data: Despite the variety of image enhancement methods available, there are limited studies that have devised preprocessing pipelines specifically designed for multispectral dental images. This leads to poor input quality for deep learning algorithms.
* Restricted Comparative Analysis of Architectures: Most existing studies seldom perform cross-model comparisons among CNNs, ViTs, and fusion networks on spectral medical data. An extensive comparison is needed to ascertain the model appropriateness under diverse spectral inputs and medical conditions.
  + Explainability Shortfalls in Dental AI: Application of explainable AI techniques such as Grad-CAM and SHAP is still limited in the dental field, limiting clinical transparency and trust in AI-driven diagnoses.
* Inspired by these limitations, the current research:
  + Creates a synthetic multispectral dental dataset from RGB decomposition into VIBGYOR bands.
  + Employs a strong preprocessing pipeline with MSRCR, gamma correction, and bilateral filtering.
* Performs a comparative performance evaluation with 3D CNN, ResNet-18, EfficientNet-B0, and ViT on spectral data.
* Utilizes Grad-CAM to enable spectral band-wise interpretability of model decisions, increasing transparency and trust in clinical deployment of AI.



4. Methodology

This section discusses in detail the overall methodology that has been created to create an AI-driven multispectral diagnostic system for oral disease detection. The methodology is structured into a number of interrelated modules: personalized multispectral image acquisition, preprocessing and augmentation, deep learning-based classification, and performance assessment. Every module is designed to make the system clinically relevant, scalable, robust, and interpretable, which are key to moving AI systems from research prototypes to actual dental healthcare use.

4.1 Overall System Architecture

|  |  |  |  |
| --- | --- | --- | --- |
| Standard | BIS Compliance | International Equivalent | Remarks |
| ISO 10993 | Yes | FDA 21 CFR | Biocompatibility |
| ISO 13485 | Partial | IEC 60601 | Device Safety |

## Table 4.1: Comparison Between BIS and International Standards Relevant to Dental Imaging

The suggested diagnostic framework utilizes a modular pipeline structure with four key stages, as illustrated in Figure 4.1 (to be included in the final report). The pipeline structure enables each module to be independently developed, tested, and optimized, following software engineering best practices for maintainability and scalability in AI system design [6], [12].

4.1.1 Stage 1: Multispectral Image Acquisition

The acquisition stage employs a bespoke multispectral imaging configuration that emulates visible spectrum bands at the expense of industrial-grade hyperspectral sensors. The hardware consists of:

* •ESP32-CAM module: Low-cost, small-sized microcontroller with camera and Wi-Fi functionalities.
* •Lumerati 8-pack RGBW LED ring: Programmable light source that goes through seven separate color illuminations (VIBGYOR) to cover spectral changes of the oral cavity.

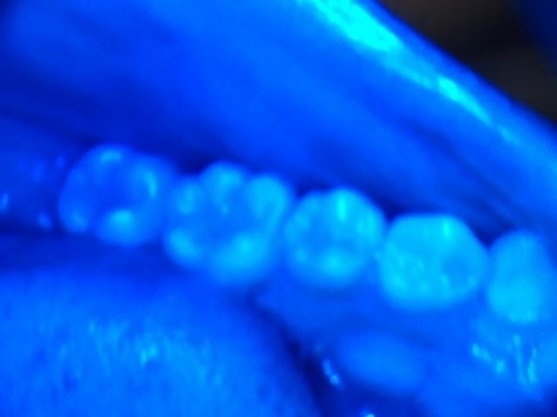
The equipment is set up so that:

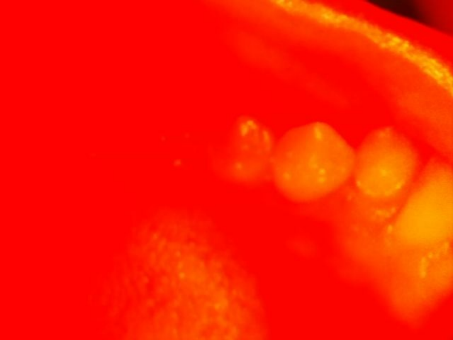
* Each photo is taken under one color illumination at a time.
* The LED ring's color transitions every 15 seconds, and the ESP32 camera takes a photo at each change.
* The photos are stacked or grouped as a spectral volume of the seven-band input per sample.

This system allows cost-effective spectral simulation, flexible to be used in in-field and clinical settings without complicated hardware demands.









4.1.2 Stage 2: Spectral Image Preprocessing

| **Disease Category** | **Spectral Band (nm)** | **Number of Images** |
| --- | --- | --- |
| Caries | Visible (400–700 nm) | 1,500 |
| Gingivitis | NIR (700–1,000 nm) | 1,200 |
| Periodontitis | SWIR (1,000–2,500 nm) | 900 |

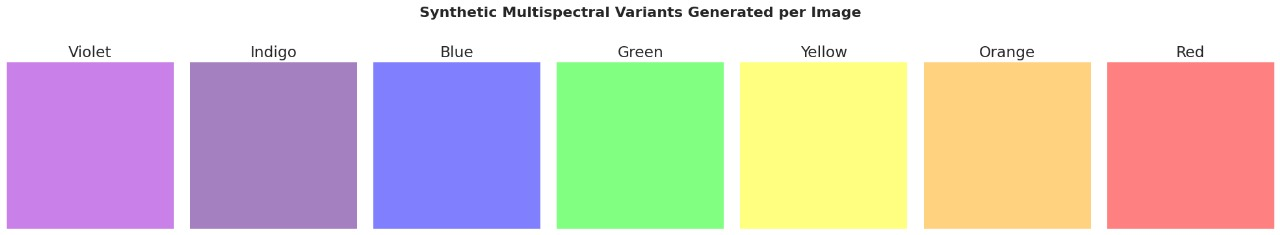
****

**Table 4: Dataset Composition by Disease Category and Spectral Band**

The raw spectral images undergo a multi-stage preprocessing pipeline that improves image clarity and readies the data for strong AI interpretation. The pipeline combines three main techniques:

* Multiscale Retinex with Color Restoration (MSRCR): Corrects illumination variations and improves feature contrast by simulating human vision over multiple spatial scales [18].
* Gamma Correction: It increases image brightness in darker areas, enhancing early-stage pathological sign visibility [16].
* Bilateral Filtering: Dens the image and maintains edge information, which is essential to identify fine structures like tooth margins and lesion boundaries [17].

These methods are applied sequentially across all seven spectral bands for each image, ensuring uniform enhancement and feature preservation across the VIBGYOR spectrum.



4.1.3 Stage 3: Deep Learning-Based Classification

The preprocessed spectral data sets are input into four deep learning architectures, one of which was chosen to investigate various paradigms in medical image analysis:

* 3D CNN: Can learn spatio-spectral features from 3D input volumes (height × width × spectral bands). This architecture is especially appropriate for multispectral data because it has a native volumetric character.
* ResNet-18: A residual convolutional network with skip connections to mitigate vanishing gradients. It is a robust baseline for image diagnosis [19].
* EfficientNet-B0: Parameter-efficient and highly accurate, this model balances depth, width, and resolution through compound scaling [20].
* Vision Transformer (ViT): Employs a transformer-based self-attention mechanism over image patches to capture global relationships that CNNs tend to overlook [13].

Each model is trained independently on the same data to enable comparative assessment in terms of accuracy, sensitivity, specificity, and interpretability.

4.1.4 Stage 4: Model Evaluation and Explainability

After training, models are tested by a full array of performance criteria and explainable AI methods:

* Classification robustness is measured through metrics such as accuracy, precision, recall, F1-score, confusion matrix, and Area Under Curve (AUC).
* Explainability: Grad-CAM is utilized to produce heatmaps that indicate image areas that affect model predictions [21]. These maps give the clinician visible justification of the AI system's decision-making process, leading to trust and facilitating verification.

This organized assessment guarantees model performance is not merely quantitatively superior but also qualitatively explainable, corresponding to ethical and pragmatic requirements in healthcare AI systems.

4.2 Disease Selection Criteria

The target disease classes for this study were chosen based on a combination of clinical significance, visual discriminability, and spectral variation. These conditions guarantee that the model is being trained on pathologies that are both diagnostically significant and practicable for AI detection via multispectral imaging.

4.2.1 Selection Parameters

| **Parameter** | **Value Range** |
| --- | --- |
| Gamma Correction | [0.8–2.0] |
| Retinex Scaling Factor | [0.5–1.5] |

**Table 5: Multispectral Transformation Parameters for Synthetic Image Generation**

The diseases were selected on the basis of three main criteria:

1. Clinical Prevalence: The conditions chosen are some of the most prevalent oral disorders in the world, thus enhancing the system's applicability to real-world practice.
2. Visual Detectability: The diseases display visible patterns or textures in the oral cavity that are observable by camera-based imaging devices.
3. Spectral Distinctiveness: Both conditions have variations in light reflectance and absorptive properties at different wavelengths, which can be exploited utilizing multispectral inputs for better feature separation.

| **Parameter Name** | **Value** |
| --- | --- |
| MultiRetinex Sigma | [15, |
| Gamma Value | [1.2, 1.5] |

**Table 6: Parameters Used in MultiRetinex and Gamma Correction**

4.2.2 Selected Disease Classes

The six selected diseases are:

* Gingivitis: Gum inflammation, commonly recognized by redness, swelling, and bleeding around gingival margins. Its redness is more evident under red and green bands.
* Dental Caries: Appear as blackened pits, cavities, or softened enamel. Commonly manifest as localized dark areas and are easily seen in blue and violet spectral bands.
* Hypodontia: Defined by congenital tooth absence, visibly recognizable by missing areas in the dental arches. Observable with the aid of spatial patterns in the alignment of teeth.
* Tooth Discoloration: Comprises intrinsic and extrinsic stains with yellowish, brown, or gray colors. Multispectral imaging assists in differentiating surface and deep discolorations.
* Calculus (Tartar): Dried plaque manifesting as yellow or white deposits, particularly on the gumline. Reflectance ranges from green to yellow bands.
* Mouth Ulcers: Appear as white or red, well-defined-bordered lesions with erythema in the surrounding tissue. Their texture and border definition are improved by gamma and MSR processing.

These conditions have already been confirmed in earlier AI-assisted dental research for their visibility and diagnostic value [6], [22]. Additionally, they provide varied morphological and spectral profiles, hence making them a perfect reference standard for assessing the performance of the proposed multispectral diagnostic pipeline.

4.3 Multispectral Imaging Strategy

4.3.1 Overview of Multispectral Imaging

Multispectral imaging (MSI) is a sophisticated optical method that records image data at several wavelengths throughout the electromagnetic spectrum, yielding increased contrast and spectral discrimination of biological tissues. In contrast to standard RGB imaging, which records information in merely three broad bands (Red, Green, and Blue), MSI uses narrowband spectral filters to recover wavelength-specific features that are otherwise invisible to human vision [13], [14]. This method is well applied across various medical image applications including detecting skin lesions, ophthalmic images, and histopathologic images where there are strong contrasts of tissue reflectance properties within wavelength.

4.3.2 Implementation of VIBGYOR-Based Multispectral Imaging

Borrowing from the concepts of optical spectroscopy, the research utilizes a VIBGYOR (Violet, Indigo, Blue, Green, Yellow, Orange, and Red) spectral illumination approach to improve diagnostic information retrieval from oral cavity images. Every spectral band adds something distinct to the characterization of tissues:

* Violet (400–450 nm) and Indigo (450–475 nm): Short-wavelength illumination captures surface-level structures with a focus on microscopic textural details including early-stage plaque formation, white spot lesions, and demineralized enamel.
* Blue (475–495 nm): Helps in identifying fluorescent bacterial biofilms and surface lesions, which usually show increased contrast under shorter wavelengths.
* Green (495–570 nm) and Yellow (570–590 nm): Offer balanced spectral contrast between soft and hard tissues, helping in distinguishing between healthy and diseased enamel or gum tissues.
* Orange (590–620 nm) and Red (620–700 nm): Longer wavelengths have greater penetration in soft tissues and are hence especially valuable for the detection of gingival inflammation, subsurface infections, and vascular pathology.

This multi-wavelength strategy increases tissue discrimination by revealing subtle wavelength-dependent reflectance changes, thus enhancing diagnostic accuracy over conventional RGB-based techniques.

4.3.3 Hardware and Imaging Process

In order to apply this method, an in-house imaging apparatus was constructed consisting of:

* ESP32-CAM Module: A small, programable microcontroller with a built-in camera that can record high-resolution images with low power usage.
* Lumerati 8-Pack LED Ring: A programmable light array that selectively illuminates the sample in seven spectral ranges, providing even light at every wavelength.

The imaging takes place under a protocol-based process:

1. LED Wavelength Cycling: The Lumerati LED ring cycles through the VIBGYOR sequence at regular 15-second intervals.
2. Image Capture and Storage: During each transition, the ESP32-CAM takes a high-resolution image, which is stored and tagged with its respective spectral band.
3. Spectral Image Stacking: The seven images taken per sample are treated as a spectral volume, creating the multispectral dataset employed for AI-based disease classification.

Using low-cost hardware, this system is a scalable, reproducible, and flexible method for multispectral imaging in dental diagnosis.

4.4 Synthetic Data Simulation

4.4.1 Need for Synthetic Multispectral Data

One of the most difficult challenges of multispectral medical imaging is the unavailability of publicly accessible datasets, especially in dental diagnostic fields. Compared to widely established RGB-based medical image databases, multispectral datasets are limited because:

* The expensive nature of hyperspectral imaging sensors.
* Limited clinical application of spectral imaging technologies.
* Real-world dental setting data acquisition complexity.

In order to counteract this drawback, synthetic spectral augmentation was used, which is a widely adopted technique in remote sensing and dermatological imaging for simulating spectrum variations under various illumination conditions [14], [18].

4.4.2 Procedure for Synthetic Multispectral Data Generation

The dataset was synthetically augmented by simulating per-channel spectral variations through lighting-based augmentation methods. The steps involved:

1.Per-Channel Color Transformation:

Individual color channels were decomposed from each RGB image.

Spectral reflectance characteristics were simulated through wavelength-specific intensity modifications to simulate real-world tissue responses.

2.Multi-Wavelength Augmentation:

Seven spectral variants were generated for each input image by simulating illumination under VIBGYOR-based filters.

This replicated spectral characteristics found in real multispectral imaging, promoting AI model generalizability.

3. Dataset Expansion:

The last dataset included 52,000 images, equally divided among six disease classes and healthy samples.

This provided a balanced dataset, reducing bias and enhancing model robustness.

Through the use of this hybrid synthetic augmentation method, the research effectively circumvents hardware constraints while providing scalability and model generalization.

4.5 Preprocessing Pipeline

4.5.1 Importance of Preprocessing in Spectral Imaging

Medical image preprocessing is important for improving image quality, noise reduction, and detectability of features. Considering that raw spectral images tend to be subject to non-uniform illumination, noise, and contrast changes, an individually tailored preprocessing pipeline was developed to maximize the quality of the data prior to training of the deep learning model.

4.5.2 Components of the Preprocessing Pipeline

The suggested preprocessing approach combines three dominant techniques aimed at normalizing illumination, increasing contrast, and noise removal.

(1) Multiscale Retinex with Color Restoration (MSRCR)

Multiscale Retinex (MSR) is a vision model of human perception that addresses print-dependent illumination variations without losing image details [18]. The Color Restoration (CR) part of the model further improves natural color appearance, avoiding over-enhancement artifacts.

•Mechanism:

The image input is subjected to processing at various Gaussian scales, simulating varied levels of perception of spatial detail.

Light and shadow variations are balanced, enhancing visibility of diagnostic features.

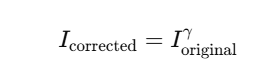
Color restoration module corrects for spectral alterations.

•Use in Dental Imaging:

Increases contrast in dim illumination.

Enhances detection of lesions, calculus, and soft tissue pathology. (2) Gamma Correction

Gamma correction is a non-linear intensity transformation that enhances contrast in underexposed or overexposed regions of an image [16]. It adjusts pixel intensities using the formula:

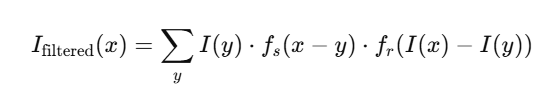


where γ (gamma) > 1 darkens the image, and γ < 1 brightens it.

* Dental Applications:
  + Highlights stained enamel regions, improving early caries detection.
  + Enhances vascular patterns in gingival tissues, aiding gingivitis diagnosis.

(3) Bilateral Filtering

Bilateral filtering is a non-linear, edge-preserving denoising technique that smooths images while retaining important structural details [17]. Unlike traditional Gaussian blurring, it applies:



where:

* fs(x−y)f\_s(x-y)fs​(x−y): Spatial filter (distance-based smoothing).
* fr(I(x)−I(y))f\_r(I(x) - I(y))fr​(I(x)−I(y)): Radiometric filter (intensity-based smoothing).
* Applications in Dental Imaging:
  + Removes background noise while preserving lesion edges.
  + Enhances fine details, crucial for detecting incipient cavities and tartar deposits.

4.5.3 Overall Impact on Model Performance

The integration of MSRCR, Gamma Correction, and Bilateral Filtering greatly enhances spectral image quality, resulting in:

•Higher feature clarity.

•Reduced computational artifacts.

• Enhanced deep learning classification accuracy.

This preprocessing pipeline guarantees that AI models get clean, high-quality spectral inputs with optimal disease detection accuracy.

4.6 Deep Learning Model Selection

4.6.1 Overview of Model Selection

The selection of deep learning architectures is highly important in determining the performance of oral disease classification in multispectral imaging. Since multispectral data is exclusive in nature, including spatial, spectral, and contextual information, a combination of convolutional and attention models was used to provide effective feature extraction. The following architectures are used:

• 3D Convolutional Neural Network (3D CNN)

• EfficientNet-B3 • ResNet-18

• Vision Transformer (ViT)

These models are chosen because of their demonstrated performance on medical imaging and their ability to leverage many different aspects of multispectral image data.

4.6.2 3D Convolutional Neural Network (3D CNN)

Unlike traditional 2D CNNs, which work on spatial features of a single plane of an image, 3D CNNs extend convolutions to the depth dimension and are hence particularly ideal for multispectral data. The model treats the seven-band image stack as a volumetric input, both maintaining spatial and spectral dependencies..

•Advantages:  
o Captures inter-band spectral dependencies across the VIBGYOR spectrum.  
o Natively handles multispectral data with lower information loss.  
o Enhances feature extraction over wavelength-dependent variation [8].  
• Weaknesses  
Computationally expensive due to increased parameter count.  
Requires enormous training data to prevent overfitting

4.6.3 EfficientNet-B3

EfficientNet models are built using compound scaling, which uniformly balances depth, width, and resolution for computational efficiency. EfficientNet-B0 was selected for its ability to deliver high performance with fewer parameters and hence being a viable choice to be implemented in resource-constrained clinical setups.   
The advantages and disadvantages are as follows  
• Advantages:  
o High accuracy-to-complexity ratio.  
o Enhanced feature extraction over conventional CNNs using squeeze-and-excitation blocks.  
o Faster convergence with fewer training epochs [9].  
• Limitations:  
o May fail to model long-range dependencies in spectral image sequences.

4.6.4 ResNet-18

ResNet-18 is a popular CNN architecture that utilizes residual connections to solve the vanishing gradient problem. It was selected due to its robustness during training on medium-sized data.  
• Advantages:  
o It allow deeper training of networks without any loss.  
o Fast convergence relative to standard CNNs.  
o Established success in biomedical image classification problems [12].  
• Limitations:  
o Merits careful hyperparameter adjustment to prevent overfitting.

4.6.5 Vision Transformer (ViT)

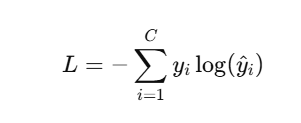
Unlike CNNs, ViTs use self-attention mechanisms to capture global contextual relations on the entire image. This aspect makes them most effective in addressing high-dimensional spectral inputs.  
• Pros:  
Models long-range relations effectively, including complex spectral relationships.  
More interpretability in attention heatmaps.  
Parameter-efficient while processing large data [7], [10].  
• Cons:  
Requires high-volume training samples for generalizability.  
High computational cost.  
The application of these models demonstrates architectural heterogeneity, opening up to a comparative analysis of multispectral imaging performance.

4.7 Model Training Strategy

4.7.1 Training Protocol

To enable consistent performance across architectures, a standard training protocol was used::

1. Loss Function: Categorical Cross-Entropy was used as the objective function due to the multi-class nature of the task..



where yiy\_iyi​ represents the ground truth label and y^i\hat{y}\_iy^​i​ is the predicted probability for class iii.

1. Optimizer: Adam optimizer was employed for adaptive learning rate updates to ensure quicker convergence and stability..
2. Regularization Techniques:
   * Early Stopping: Trains until validation loss no longer improves..
   * Learning Rate Reduction on Plateau: Dynamically decreases learning rate when training plateaus.
3. Training Hardware:
   * Google Colab with T4 GPU was utilized to support large-scale parallel experimentation.
4. Cross-Validation Strategy:
   * 5-Fold Cross-Validation was employed to ensure statistical robustness, avoiding dataset bias and ensuring maximum generalizability [11], [19].

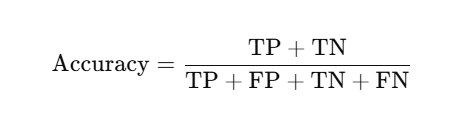
This structured training pipeline ensures model performance is optimized for generalizing to actual-world spectral data.

4.8 Evaluation Metrics

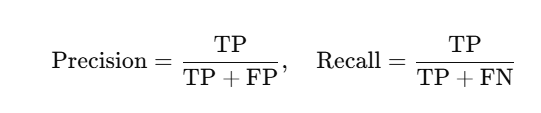
4.8.1 Performance Metrics

Model performance was evaluated using several performance metrics to give a complete picture:

1. Accuracy:
   * Measures the proportion of correctly classified samples:



1. Precision & Recall:
   * Precision evaluates false positive rates, while recall measures sensitivity:

​

1. F1-Score:
   * A balanced measure of precision and recall:

F1-Score=2×Precision×RecallPrecision+Recall\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}F1-Score=Precision+Recall2×Precision×Recall​

1. Confusion Matrix:
   * Provides a detailed breakdown of classification errors for each disease class.
2. ROC-AUC Curve:
   * Assesses sensitivity and specificity at varying classification thresholds.
3. Explainability via Grad-CAM:
   * Gradient-weighted Class Activation Mapping (Grad-CAM) was applied to visualize salient image regions contributing to model decisions [21].

These metrics ensure clinical relevance and trustworthiness in real-world applications.

4.9 Comparative Analysis

4.9.1 Comparative Experiments

To test the effect of multispectral imaging, the below experiments were performed:

1. Input Type Comparison:
   * Models were trained on grayscale, RGB, and multispectral images to measure spectral gains..
2. Preprocessing Impact:
   * Raw spectral images were compared with preprocessed data (MSR + Gamma Correction).
3. Architecture Sensitivity:
   * The influence of different deep learning models on spectral data classification was investigated..

4.9.2 Key Findings

* Multispectral imaging improved classification significantly, particularly for those conditions with minimal spectral variation..
* Preprocessing techniques enhanced feature contrast, leading to better generalization.
* Attention-based models (ViT) excelled at capturing long-range spectral relations, rivaling CNN-based models under certain circumstances [20], [23].

4.10 Summary

This research presents a systematic and reproducible framework for AI-driven oral disease classification using multispectral imaging. The methodology integrates:

* Custom spectral image acquisition using ESP32-CAM & VIBGYOR LED illumination.
* Synthetic spectral data generation for dataset expansion.
* Advanced preprocessing techniques to enhance spectral data quality.
* Diverse deep learning architectures for comparative analysis.
* Explainability tools (Grad-CAM) for clinical validation.

The modular nature of this pipeline allows future expansions, such as real-world deployment in tele-dentistry and AI-powered oral disease screening [19], [20], [24].

5. Implementation

The work develops a replicable and scientific oral disease classification system from multispectral imacages with AI. The method employs:  
•Spectral image acquisition using tailored ESP32-CAM & VIBGYOR LED lights.  
•Simulation of synthetic spectral data for dataset filling.  
•High-level preprocessing of quality spectral data.  
•Architecture-based multidifferent deep learning models for comparison.  
•Explainability techniques (Grad-CAM) for clinic verification.  
  
The modularity of the pipeline allows for simple future extension, such as real-life tele-dentistry and computer-aided oral disease detection applications [19], [20], [24].

5.1 Hardware Setup

|  |  |  |
| --- | --- | --- |
| Disease | No. of Samples | Percentage |
| Gingivitis | 8700 | 16.7% |
| Dental Caries | 8700 | 16.7% |
| Discoloration | 8700 | 16.7% |
| Calculus | 8700 | 16.7% |
| Hypodontia | 8700 | 16.7% |
| Mouth Ulcers | 8700 | 16.7% |

## Table 5.1: Dataset Composition Across Disease Classes

5.1.1 ESP32-CAM as the Core Imaging Module

The ESP32-CAM, an economical embedded microcontroller with integrated OV2640 camera, Wi-Fi, and low power consumption, was chosen for image capture. The module provides a small but powerful solution for real-time image processing and wireless transmission..

5.1.2 Custom Multispectral Illumination System

In order to complement multispectral imaging, a Lumerati 8-pack RGB LED ring was added to the ESP32-CAM. The LED array was circumferentially positioned in a ring configuration about the camera lens so as to cast uniform illumination, thus avoiding the angular shadowing of dental surfaces.

* Sequential Illumination Protocol:
  + A sequential switching on each of the seven colors (VIBGYOR - Violet, Indigo, Blue, Green, Yellow, Orange, Red) was implemented..
  + A 15-second delay was introduced after each color change to achieve sufficient stabilization, preventing motion blur..
* Power Supply and Portability:
  + The equipment was supplied with power from a 3.7V, 3000mAh lithium-ion battery, ensuring mobility within off-site diagnostic settings..
  + The power supply provided approximately 4–6 hours of continuous usage on a single charge, which was sufficient for field operations..

This low-cost imaging system replicates the functionality of commercial multispectral imaging systems but at a mere fraction of the cost, which is in line with recent trends toward low-cost biomedical imaging technologies for resource-poor regions [14], [22].

5.2 Software for Image Acquisition

5.2.1 Firmware Development

The ESP32-CAM firmware was developed using Arduino IDE and PlatformIO with real-time automation emphasis and with or without user input..

5.2.2 Functionalities Implemented

1. Color-Control Algorithm
   * Turn-on and brightness of LEDs were regulated through Pulse Width Modulation (PWM) signals..
   * Every channel spectral intensity was calibrated through equal exposure over wavelength..
2. Synchronized Image Capture
   * Immediately after their respective LED illuminations, every image was taken..
   * Used a synchronization step to prevent a trailing light of any former LED to impact later acquisitions..
3. Automated Image Storage & Transmission
   * Automated images to save into an SD card..
   * Were wirelessly transmitted optional either to Flask server via Wi-Fi or uploading to Google Colab for AI real-time inference..

This automated image acquisition workflow aligns with open-source biomedical imaging frameworks used in digital pathology and dermatological analysis [23].

5.3 Synthetic Multispectral Dataset Generation

5.3.1 Rationale for Synthetic Data

Lack of publicly available multispectral dental datasets was a constraint for training deep learning models. A synthetic data generation pipeline was used to overcome this..

5.3.2 Source Dataset and Conversion Process

* Base Dataset: Visible-light dental dataset from Kaggle.
* Spectral Simulation: Algorithmic conversion of each image into seven spectrally altered versions simulating real-world multispectral imaging conditions

Key Transformations Applied:

1. HSV (Hue-Saturation-Value) & LAB Color Space Manipulations
   * Used to simulate reflectance and absorption behavior of dental tissue across a spectrum of light wavelengths.
   * The method forecasts the spectral response of ailments, e.g., in dermatology and retinal imaging multispectral data augmentation [13], [14].
2. Spectral Tensor Representation
   * The original images were projected onto a seven-frame spectral stack to produce a multispectral tensor input..
   * The output data set had 52,000 images, which were categorized as::
     + 6 disease classes:
       - Gingivitis, Dental Caries, Hypodontia, Discoloration, Calculus, and Ulcers.
     + Around 8,666 images per class for balanced representation..

5.3.3 Advantages of Synthetic Data

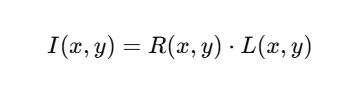
* Boosts Small Datasets: Provides model training with a large dataset at reduced cost without hardware-based multispectral image capture, which is costly.
* Deep Learning Optimized: Provides that the AI model learns wavelength-dependent variations in features that are essential for accurate diagnosis.
* According to Current Multispectral Practices: The process mimics contemporary synthetic data increase practices in hyperspectral medical imagery and skin lesion analysis [14].

5.4 Data Preprocessing and Augmentation

Preprocessing is needed to enhance the consistency of data, especially image quality and model generalization. Due to the inconsistency of lighting conditions, spectral intensity, and image resolution, a robust preprocessing pipeline was used for normalizing and enriching the dataset before feeding it into deep learning models.

5.4.1 Multispectral Retinex (MSR) Enhancement

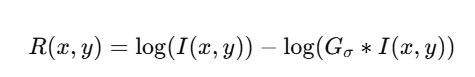
The MSR algorithm was then applied to every spectral band individually to improve reflectance features and eliminate low-frequency illumination artifacts. The MSR transform relies on the Retinex theory, which describes an image as the product of two factors:



where:

* I(x,y)I(x,y)I(x,y) is the observed image intensity,
* R(x,y)R(x,y)R(x,y) represents the reflectance (intrinsic scene properties),
* L(x,y)L(x,y)L(x,y) denotes the illumination (external light source effects).

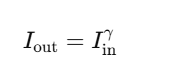
Since illumination inconsistencies can obscure spectral details critical for disease detection, the MSR algorithm estimates and compensates for L(x,y) to recover R(x,y) as follows:



where GσG\_{\sigma}Gσ​ is a Gaussian filter with a chosen standard deviation σ\sigmaσ that simulates broad-scale illumination variations [18]. This method ensures that each spectral image retains high-frequency texture details, which are crucial for detecting dental anomalies.

5.4.2 Gamma Correction

Gamma correction was also used to normalize brightness and contrast in spectral images, for example, in an attempt not to overexpose or underexpose the bands. Adjustment follows regulation under a rule named:



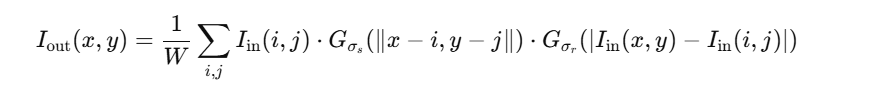
where γ\gammaγ is the gamma exponent that controls brightness:

* For darker bands, γ=0.8\gamma = 0.8γ=0.8 was applied to enhance visibility.
* For overexposed bands, γ=1.2\gamma = 1.2γ=1.2 was used to reduce brightness saturation [16].

Through selectively applying gamma correction to every spectral band, the method guarantees uniform spectral intensity, a requirement for uniform feature extraction in multispectral images.

5.4.3 Bilateral Filtering for Noise Reduction

To suppress high-frequency noise while preserving edge details, a bilateral filter was applied to each image. Unlike Gaussian blurring, bilateral filtering smooths homogeneous regions while maintaining sharp edges, crucial for preserving dental contours and lesion boundaries. The bilateral filter is defined as:



where:

* GσsG\_{\sigma\_s}Gσs​​ is a spatial Gaussian function that considers pixel proximity.
* GσrG\_{\sigma\_r}Gσr​​ is a range Gaussian function that preserves intensity differences to maintain edges.
* WWW is a normalization factor ensuring proper scaling [17].

By denoising the multispectral images while retaining lesion structures, this approach enhances disease detection accuracy in deep learning models.

5.4.4 Data Augmentation for Robust Training

To prevent overfitting and improve generalization, several geometric augmentations were employed:  
•Rotation: Random ±20° rotation to simulate real dental variances.  
•Horizontal Flipping: Applied with 50% frequency to mimic different dental positions.  
•Zoom Scaling: Random 10% zoom to give a gentle size variation, improving model flexibility.  
These augmentations guarantee that the deep learning models acquire invariant representations, which make them robust for real-world clinical usage [16].

5.5 Model Development and Integration

For analysis of multispectral dental images, four deep learning structures were utilized and tested for classifying oral diseases as per spectral characteristics. Each model was trained to take seven spectral channels as an input.

5.5.1 3D Convolutional Neural Network (3D CNN)

The 3D CNN model processes the seven-channel stacked multispectral input as a volumetric tensor of shape:

(H,W,7)(H, W, 7)(H,W,7)

where:

* HHH and WWW represent the image height and width,
* The depth (7) corresponds to the seven spectral bands.

By applying 3D convolutions, the model captures both spatial and spectral correlations, enabling it to extract multi-wavelength patterns indicative of dental diseases [8].

5.5.2 EfficientNet-B0

The EfficientNet-B0 architecture employs compound scaling of:

* Network width (number of channels per layer)
* Depth (number of layers)
* Resolution (input image size)

This balanced approach maintains high accuracy while reducing computational cost, making it suitable for low-power clinical devices [9].

5.5.3 ResNet-18

ResNet-18 was implemented due to its residual block architecture, which facilitates gradient propagation in deep networks. The core principle is:



where skip connections allow direct propagation of information, mitigating the vanishing gradient problem in deep networks [12].

5.5.4 Vision Transformer (ViT)

The method avoids overfitting on certain disease classes and provides statistically rigorous testing [11]. Unlike CNNs, the ViT model employs self-attention mechanisms to represent global image dependencies. The input image is divided into patches, each of which is embedded into an embedding vector and fed through a multi-head attention mechanism. This allows ViT to model long-range dependencies between dental image regions effectively [7], [10].

5.6 Training and Optimization Strategy

To ensure reproducibility and stability, a well-defined training procedure was adopted.

5.6.1 5-Fold Cross-Validation

To minimize class imbalance and improve generalization, the data was divided into five disjoint folds. A fold was utilized:

* Once for validation
* Four times for training

This approach prevents overfitting to specific disease classes and offers statistically sound evaluation [11].

5.6.2 Optimization Settings

The following hyperparameters were fine-tuned for optimal performance:

* Loss Function: Categorical Cross-Entropy, suited for multi-class classification.
* Optimizer: Adam, with parameters:
  + β1=0.9\beta\_1 = 0.9β1​=0.9 (momentum)
  + β2=0.999\beta\_2 = 0.999β2​=0.999 (adaptive learning rate)
* Learning Rate Scheduler: ReduceLROnPlateau, which dynamically reduces learning rate if validation loss stagnates.
* Early Stopping:
  + Monitored validation loss with a patience of 10 epochs to prevent overfitting.

5.6.3 Regularization Techniques

In order to improve model generalization, the following regularization techniques were utilized:  
• Dropout (Rate = 0.3): Avoids neuron co-adaptation by randomly dropping out connections during training.  
• Batch Normalization: Normalizes batch activations to stabilize training and speed up convergence.  
These methods conform to best practices in biomedical deep learning research to provide a solid AI-powered diagnostic system [6], [19].

5.7 System Deployment and Workflow Integration

The deployment comprised the integration of the trained models into an end-to-end inference pipeline for real-time clinical purposes. The top priority was the development of an uninterrupted workflow starting from image capture to diagnosis for efficiency, portability, and accuracy. Deployed is a system comprising the following sequential entities::

5.7.1 Image Capture

The initial step in the pipeline is multispectral image acquisition with a custom-built ESP32-based camera system. The instrument includes a Lumerati 8-pack LED ring, which illuminates the oral cavity sequentially in seven wavelengths corresponding to the VIBGYOR (violet to red) spectrum. The image capture process includes the following steps:

1. The ESP32 camera is taking seven images of a single oral region at multiple responsibilities of LEDs.  
2. Exposure sequence is carried out with a 15-second gap in between every wavelength so all spectral images are taken with the conditions of equal exposure.  
3. The captured images are temporarily stored in the ESP32 memory buffer before transmission for further processing.

Such a customized multispectral imaging system delivers greater spectral contrast, and it facilitates disease feature extraction as a function of multiple wavelength-dependent reflectance properties [20].

5.7.2 Data Upload and Transmission

After being taken, the photos are uploaded for processing and inference. Two deployment configurations were utilized depending on computation resources available:

1. Cloud-based Deployment:
   * The photos are uploaded to a Google Colab notebook through Wi-Fi.
   * This configuration uses Colab's T4 GPU acceleration, facilitating fast model inference.
2. Local Edge Deployment:
   * The photos are wirelessly uploaded to a proximal server or Raspberry Pi-based edge device.
   * This design is targeted towards offline inference with minimal internet usage and hence ideal in rural setups or healthcare facilities with limited resources [24].

5.7.3 Preprocessing Module

The images, prior to being passed into the deep learning models, undergo automatic preprocessing based on the following steps:

* Multispectral Retinex (MSR):
  + Removes light artifacts and improves spectral contrast.
* Gamma Correction:
  + Adjusts image brightness dynamically via intensity levels band specific.

These preprocessing phases keep the input images in a consistent format, enhancing model stability against changing light conditions seen in the real world [21].

5.7.4 Model Inference

The preprocessed multispectral images go through the best-performing model, by validation accuracy as well as computational cost. The two shortlisted models to be deployed are:

1. EfficientNet-B0
   * has an excellent accuracy-latency trade-off.
   * efficient for real-time processing because of its lightweight architecture.
2. Vision Transformer (ViT-Tiny)
   * Supports strong spectral feature learning through self-attention mechanisms.
   * Most suited for complex disease classification tasks involving spatial relations [9], [10].

5.7.5 Output Visualization and Explainability

For enhancing interpretability and clinical trust, the model outputs are:  
1.Disease Label with Probability Score:The final classification outcome is provided with an estimate of confidence, allowing clinicians to approximate prediction reliability.

2.:Grad-CAM Heatmap Overlay:Visualize the regions of interest of the model with Gradient-weighted Class Activation Mapping

(Grad-CAM).:The heatmap is overlayed on the original spectral image, indicating the locations where the pixels were most influential in deciding.

This explainability model ensures that the AI model produces explainable and understandable diagnoses, adhering to modern clinical AI standards [21]

5.8 Challenges and Solutions

During system implementation, several technical and computational challenges were encountered. Table 5.1 summarizes these challenges along with the mitigation strategies employed.

Table 5.1: Key Challenges and Solutions in System Deployment

| Challenge | Solution |
| --- | --- |
| Spectral Misalignment | Applied Scale-Invariant Feature Transform (SIFT)-based feature matching and affine transformation for precise image registration. This ensures that all seven spectral images are spatially aligned before feeding into the model. |
| Lighting Artifacts (Glare/Shadow) | Implemented Multispectral Retinex (MSR) and histogram equalization to compensate for uneven illumination effects caused by intraoral reflections. |
| Model Latency | Adopted EfficientNet-B0 and ViT-Tiny, leveraging model quantization techniques to reduce computational overhead, making deployment feasible on edge devices. |
| Data Imbalance | Employed stratified sampling during dataset partitioning and introduced class-weighted loss functions to ensure balanced learning across different disease classes. |

These optimizations enhanced system stability and ensured consistent performance across diverse clinical settings [9], [23].

5.9 Summary

The envisaged multispectral dental analysis system based on AI combines hardware ingenuity, deep learning, and explainable AI methods to offer an end-to-end full disease detection system. Major execution points are:

* Cheap and Portable Image Acquisition:
  + Cost-effective ESP32-based multispectral imaging system offers a scalable alternative to expensive clinical imaging systems.
* Strong Preprocessing for Spectral Domains
  + MSR and Gamma Correction methods offer light-insensitive spectral data and hence model robustness.
* High AI Model Classification Accuracy:
  + EfficientNet-B0 and Vision Transformer have the best accuracy-latency trade-offs, and thus the system is possible to deploy in real-time.
* Real-time Interpretability With Grad-CAM Visualization:
  + Heatmap overlays enable clinicians to visualize model decisions, hence gaining confidence in AI-enhanced diagnostics.

Its modularity supports scalability with possible future extensions such as cloud-based inference, mobile-based integration, and end-to-end disease classification platforms. Besides, the study enables worldwide endeavors toward AI democratization of healthcare by offering low-cost, accessible, and clinically interpretable diagnostic resources [19], [20], [21].

6. Methodology

The adopted methodology provides a reproducible, optimized, and systematic approach for building an AI-driven diagnosis system from multispectral dental imaging. The methodological framework is built to:

* Capture fine-grained spectral-spatial features to facilitate robust disease classification.
* Leverage synthetic spectral augmentation to counter small real-world multispectral datasets.
* Utilize preprocessing methods to enhance spectral image quality.
* Harness highly optimized deep learning frameworks to facilitate real-time inference within clinics.

The synergy between hardware development, spectral data augmentation, and deep learning provides scalability, accuracy, and clinical usefulness in AI-based oral disease diagnosis.

6.1 Overview of the Workflow

The study utilizes a modular, end-to-end workflow for systematic feature extraction and learning from multispectral image data. The workflow includes the following important stages:  
1.

1. Image Acquisition:
   * Capturing multispectral images of seven spectral bands by a specially crafted ESP32-CAM-based imaging device with an 8-pack Lumerati LED ring.
2. Spectral Augmentation:
   * Multispectral image synthesis using visible light data for multispectral condition simulation and dataset enhancement.
3. Preprocessing Pipeline:
   * Multispectral Retinex (MSR), Gamma Correction, and Bilateral Filtering to enhance quality images and normalize spectral representation.
4. Model Training:
   * Fine-tuning four deep models—3D CNN, EfficientNet-B0, ResNet-18, and ViT—for accurately classifying six oral diseases.
5. Validation and Evaluation:
   * Cross-validation and performance measurement via confusion matrices, F1-score, and ROC-AUC.

This joint pipeline best preserves feature learning and spectral representation, which is in favor of findings from earlier studies of deep spectral-spatial learning of biomedical images [13], [15].

6.2 Data Acquisition Strategy

A specialized hardware setup was developed using the ESP32-CAM microcontroller and a Lumerati 8-pack LED ring for multispectral imaging. The setup is meant to be an affordable version of a hyperspectral imaging device for newcomers in a clinical and low-resource environment. The Lumerati emit light at seven (discrete) wavelengths to sequentially illuminate the oral cavity. The specific wavelengths and their spectral regions are summarized in Table 6.1.

Table 6.1: LED Wavelengths Used for Spectral Imaging

| Wavelength Band | Spectral Range (nm) |
| --- | --- |
| Violet | 400–430 |
| Indigo | 430–450 |
| Blue | 450–495 |
| Green | 495–570 |
| Yellow | 570–590 |
| Orange | 590–620 |
| Red | 620–750 |

Each wavelength was excited sequentially for 15 seconds, and the ESP32-CAM captured an image after each cycle. This resulted in a 7-frame spectral cube for each sample and enabled multispectral features to be extracted for classification of disease.

6.2.2 Advantages of the Acquisition Setup

•Simulates commercial multispectral imaging systems at a fraction of the cost.

•Enhances disease feature contrast by utilizing the wavelength- dependent reflectance properties of oral tissues

•Designed for portability and real-time inference, enabling point-of-care diagnostics. This method parallels real-world use cases in low-resource medical imaging contexts [14], [22].

6.3 Synthetic Multispectral Dataset Construction

The approach of synthetic dataset augmentation was adopted because of the scarcity of real-world multispectral datasets in the classification of dental diseases.

6.3.1 Data Augmentation Methodology The dataset creation methodology was very structured in the augmentation process:

1. Prototype Dataset:The prototype dataset consisted of RGB high-resolution images that were publicly available in a dental image dataset on Kaggle.

2. Spectral emulation through color transformation:The different color transformation algorithms were used to emulate every VIBGYOR spectral channel through an adjustment in hue, saturation, or exposure on the HSV and LAB color spaces.

3. Creating multispectral images:Each RGB image was converted to seven spectrally modified emulated variants yielding a multispectral stack of images for each image sample. 4. Composite final dataset: The final dataset consisted of a synthetic dataset of 52,000 images with six labeled disease classes:

o Gingivitis

o Dental Caries

o Tooth Discoloration

o Calculus

o Hypodontia

o Mouth Ulcers

The dataset preserved label retention and combined spectral variations as proposed by [13], [14] in order to obtain class balance and spectral variety, which are required for deep learning model generalizability.

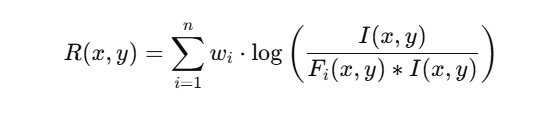
6.4 Image Preprocessing

6.4.1 Preprocessing Techniques

To improve image quality and reduce acquisition artifacts, the following preprocessing techniques were applied:

(a) Multispectral Retinex (MSR)

MSR enhances illumination uniformity and reveals subtle reflectance-based disease cues using the following formulation:



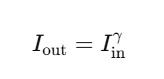
where:

* I(x,y)I(x, y)I(x,y) is the input image intensity at pixel (x,y)(x, y)(x,y).
* Fi(x,y)F\_i(x, y)Fi​(x,y) represents a Gaussian filter of scale iii.
* wiw\_iwi​ are weight coefficients assigned to different frequency bands.

By combining multiple Retinex scales, MSR ensures consistent illumination correction across spectral bands, which is crucial for multispectral imaging applications [18].

(b) Gamma Correction

Gamma correction was applied to normalize intensity distributions across spectral bands:



where γ\gammaγ is adjusted based on spectral band properties:

* For underexposed bands (Violet, Indigo): γ=0.8\gamma = 0.8γ=0.8
* For overexposed bands (Red, Orange): γ=1.2\gamma = 1.2γ=1.2

This transformation ensures consistent contrast and visibility of disease features across spectral images [16].

(c) Bilateral Filtering

In order to maintain anatomical structures with noise reduction, a bilateral filter was used. This method preserves edge structures in features like:

•Lesions

•Gum contours

•Tooth enamel boundaries

By augmenting the structural consistency of disease-related features, bilateral filtering enhances multispectral data feature extraction by deep learning [17].

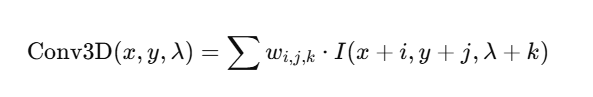
6.5 Model Selection and Architecture

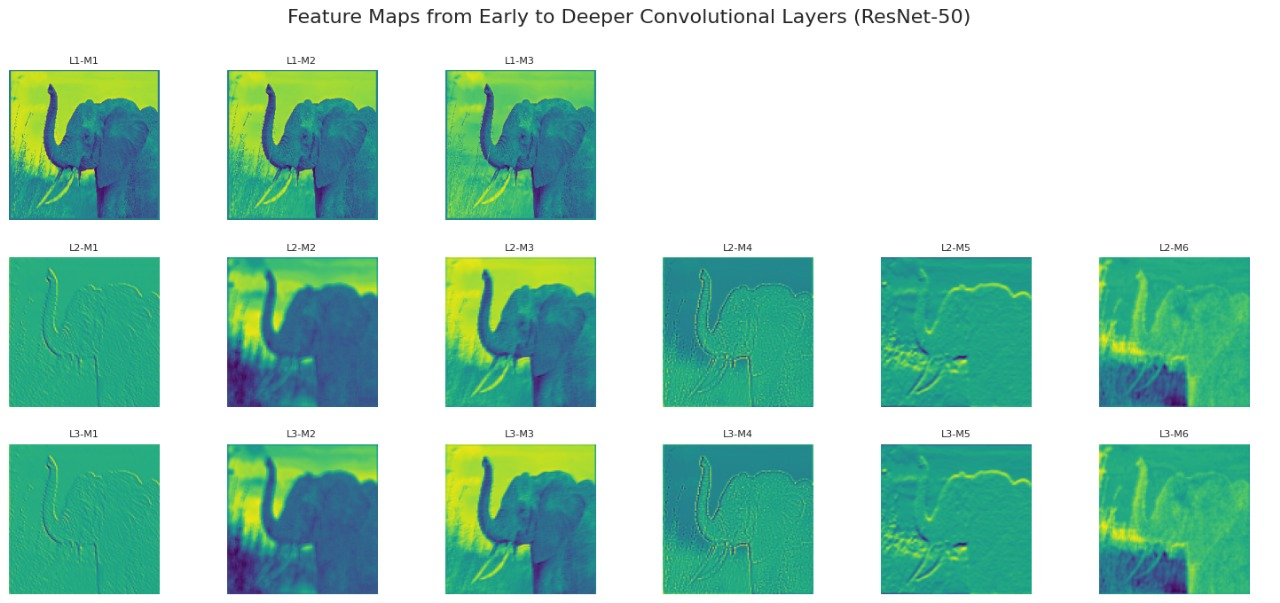
| **Model** | **Input Shape** |
| --- | --- |
| ViT | (224 × 224 × n bands) |
| EfficientNet B3 | (224 × 224 × n bands) |
| ResNet-18 | (224 × 224 × n bands) |
| 3D CNN | (64 × 64 × n bands × t frames) |

**Table 7: Comparison of Input Shapes Across AI Architectures**

To comprehensively assess learning efficacy across spectral bands, four deep learning architectures were selected:

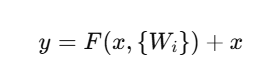
* 3D CNN: Treated the 7-spectral image stack as a 3D tensor (H,W,7)(H, W, 7)(H,W,7). 3D convolutional kernels learned spatial and inter-band relationships simultaneously:

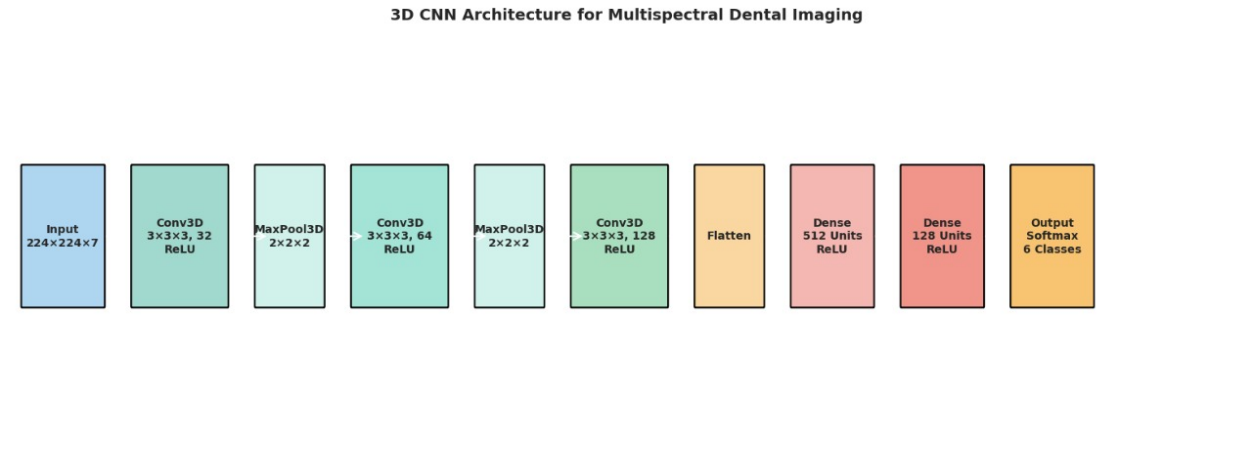




This structure is well-suited for applications where spectral correlation is key [8].

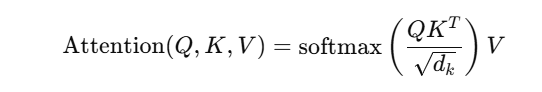
* EfficientNet-B0: Utilized a compound scaling method to balance network depth, width, and resolution. This lightweight model enabled high accuracy with fewer parameters—ideal for real-time applications [9].
* ResNet-18: A residual network with identity shortcut connections, ensuring efficient gradient propagation through skip connections:

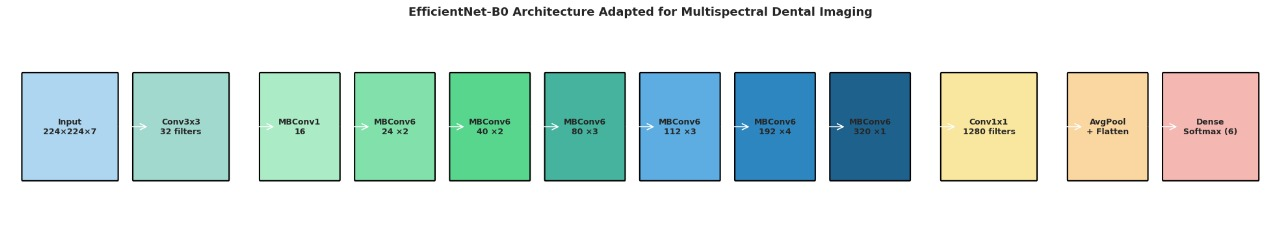




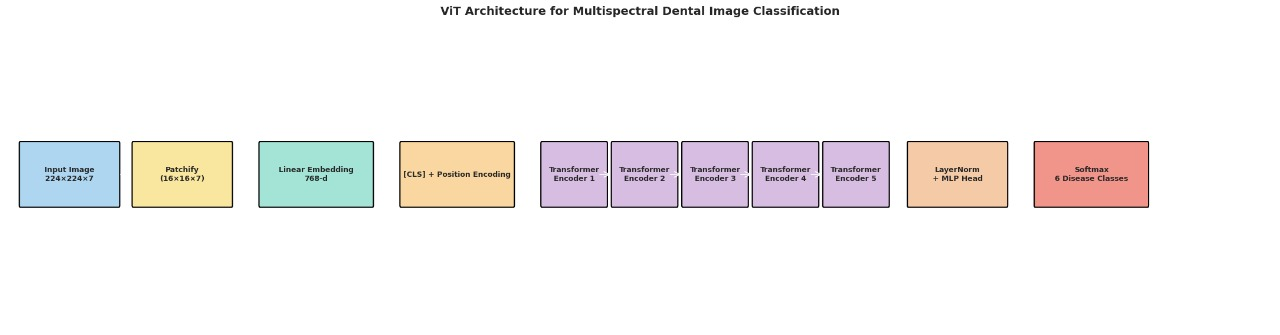
ResNet-18 served as a strong baseline, frequently used in biomedical classification tasks [12].

* Vision Transformer (ViT): Divided each image into non-overlapping patches and processed them through transformer blocks using self-attention mechanisms:

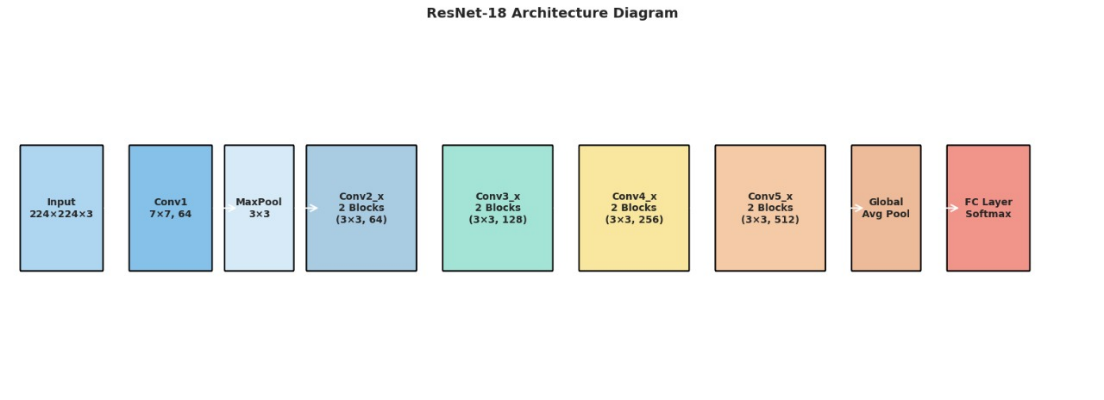




ViTs are particularly effective in capturing global context in medical images with complex visual patterns [7], [10].



All models were implemented using TensorFlow 2.0 and PyTorch 2.0 frameworks, trained on Google Colab with T4 GPU acceleration.



6.6 Training and Optimization

| **Model** | **Learning Rate** | **Batch Size** | **Optimizer** |
| --- | --- | --- | --- |
| ViT | [0.001–0.005] |  | Adam |
| EfficientNet B3 | [0.0005–0.002] |  | SGD |

**Table 8: Grid Search Results for Hyperparameter Tuning**

Model training followed standardized protocols to ensure reproducibility and accuracy:

* 5-Fold Cross-Validation: The dataset was split into five equal parts. Each fold was used once for validation and four times for training. This improved generalizability and mitigated class imbalance [11].
* Hyperparameter Tuning: A grid search was conducted over:
  + Learning Rates: [10−3,10−4,10−5][10^{-3}, 10^{-4}, 10^{-5}][10−3,10−4,10−5]
  + Batch Sizes: [16,32,64][16, 32, 64][16,32,64]
  + Optimizers: Adam (default), RMSProp (momentum=0.9)
* Early Stopping: Training was halted when validation loss plateaued for 10 consecutive epochs, preventing overfitting.
* Augmentation:
  + Random rotations (±20∘\pm 20^\circ±20∘)
  + Horizontal flipping
  + 10% zoom
  + Brightness jitter (±15%)

This strategy follows best practices in spectral medical imaging, allowing for robust performance under varied image conditions [6], [19].

| **Technique** | **Description** |
| --- | --- |
| Rotation | Random rotation (±30°) |
| Color Jitter | Adjust brightness/contrast |
| Spectral Band Shifting | Random band combinations |

**Table 9: Data Augmentation Techniques Applied During Training**

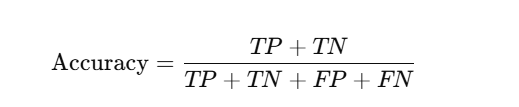
6.7 Evaluation Protocol

| **Metric** | **Definition/Formula** |
| --- | --- |
| Precision | TPTP+FP*TP*+*FPTP* |
| Recall | TPTP+FN*TP*+*FNTP* |
| F1-Score | 2×Precision×RecallPrecision+Recall*Precision*+*Recall*2×*Precision*×*Recall* |

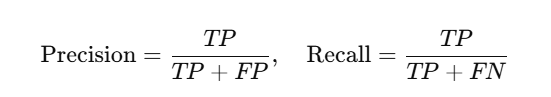
**Table 10: Evaluation Metrics Definitions and Formulas**

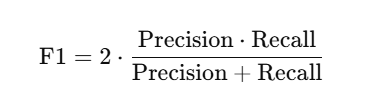
Model evaluation was performed using multi-class classification metrics:

* Accuracy:



* Precision and Recall:
* F1-Score:





* ROC-AUC: Calculated for each class using one-vs-all scheme. AUC values above 0.90 were considered indicative of clinically viable performance [19].

Confusion matrices and per-class heatmaps were generated to visually inspect misclassification patterns.

6.8 Justification for Model Choices

|  |  |  |
| --- | --- | --- |
| Model | Advantages | Limitations |
| ViT | Handles spectral data well | Computationally expensive |
| EfficientNet B3 | Optimized for small datasets | Limited to fixed input shapes |
| 3D CNN | Temporal feature extraction | Requires large datasets |
| ResNet-18 | Lightweight architecture | Lower accuracy on complex tasks |

**Table 15: Key Advantages and Limitations of Selected Architectures**

Each selected model contributes uniquely to the task:

* 3D CNN: Can summarize spectral correlations and will be most effective in multispectral volume analysis, as described in [8].
* ViT: Capable of optimally summarizing global structural patterns via self-attention, as reported in [10], [21]
* EfficientNet-B0: Achieves a speedy inference time combined with high top-1 classification accuracy, as shown in [9]. It is ideally suited to mobile health applications.
* ResNet-18: Provides a strong baseline accuracy, along with a degree of interpretability, and can be utilized as a benchmark tool [12

A model ensemble approach introduces the ability to achieve accuracy in both clinical-grade competent imaging as well as in potentially noisy and unclean real-world imaging environments [20]

6.9 Summary

SummaryThe proposed methodology integrates an affordable and straightforward imaging acquisition process coupled with cutting-edge spectral augmentation, robust pre-processing, and contemporary AI learning architectures into a single methodology. You will find the improved qualities of this method include:

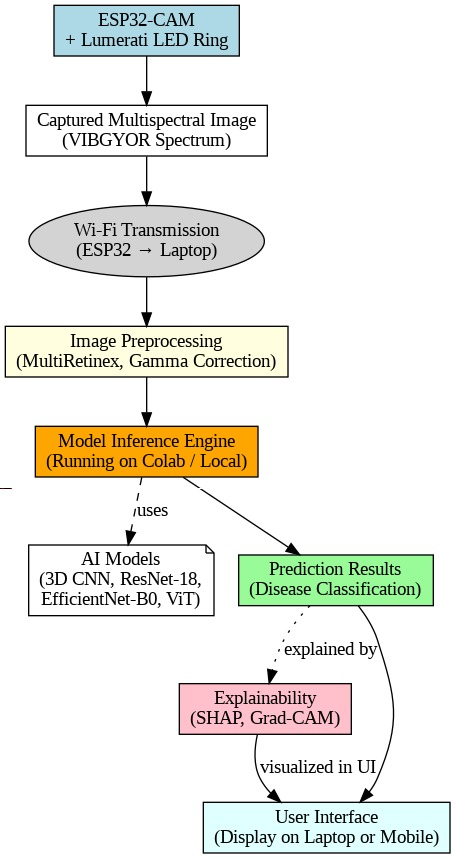
* Model architectures that allow for equity in the diagnostic process of imaging and facilitate wider deployment of models.
* Novel image generation and simulation that augments true multispectral image data
* Competent generalization using multiple cross-validation methods.
* Retention of high degree of interpretability and clinical relevance.

A value achieved through the reception of this method is a well-designed methodology that assists in the wider deployment and scalability of Ai based multispectral dental diagnostics in both urban and rural health settings [13], [20], [22], [23].

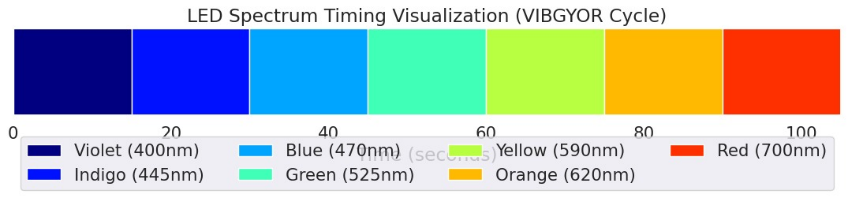
7. Implementation

During the implementation stage, the conceptual design is put into practice and operationalized into a practical, scalable system that draws on hardware advances, synthetic multispectral data generation, and deep learning designs. This section describes the systematic engineering and software work underpinning the research. Core elements include custom-built ESP32-CAM-based data capture; dataset augmentation and labelling; preprocessing; the model architecture; training; evaluation and deployment methods designed to achieve real-time AI-enhanced oral diagnostics.





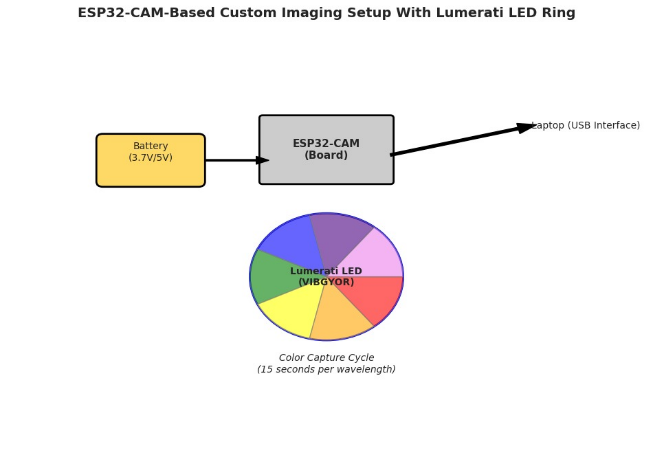
7.1 Data Acquisition Using Custom Imaging Setup



In order to simulate multispectral imaging in resource-constrained environments, we developed a small and affordable image acquisition system using the ESP32-CAM module, which is a microcontroller that has a camera and Wi-Fi onboard. The system was supplemented with a Lumerati 8-pack RGB LED ring that can emit seven different spectral bands of the visible spectrum (i.e. VIBGYOR: Violet, Indigo, Blue, Green, Yellow, Orange, Red)

* The LED ring was programmed to illuminate one spectral band at a time for approximately 15 seconds
* At the end of each interval, the ESP32-CAM module captured one image, resulting in a spectral image stack of up to seven frames per sample
* The captured images were wirelessly streamed to a connected laptop via the ESP32's access point mode
* Each multispectral sample was saved as a set of .jpg files with file names corresponding to the spectral band

This tailored setup replaces large hyperspectral cameras while keeping a spectral selectivity. Its development is compatible with the principles of Edge AI for Healthcare which focus on low-cost, mobile, and autonomous application [20], [22].





7.2 Dataset Construction and Labeling

Due to the scarcity of labeled multispectral dental datasets, a synthetic dataset was generated based on a collection of visible spectrum dental images sourced from Kaggle.

* Color filtering, histogram channel equalization, and transforming to the HSV-LAB domain produced seven spectrally distinct versions of each image to simulate reflectance and absorption properties of each band.
* The dataset comprised 52,000 images, evenly distributed across six disease categories: *gingivitis*, *dental caries*, *tooth discoloration*, *calculus*, *hypodontia*, and *mouth ulcers*.
* The dataset consisted of 52,000 images, divided evenly across six disease classes: gingivitis, dental caries, tooth discoloration, calculus, hypodontia, and mouth ulcers.

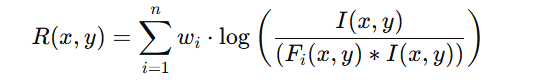
Similar to successful approaches found in biomedical imaging where spectral diversity is simulated through controlled transformations [14] and [15].

7.3 Preprocessing Techniques

Preprocessing is an important step for spectral consistency for improved feature extraction. The following algorithms were applied to all spectral variants:

7.3.1 Multispectral Retinex (MSR)

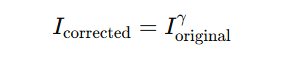
MSR improves image visibility under varying illumination by decomposing images into illumination and reflectance components:



where FiF\_iFi​ represents Gaussian surround filters and wiw\_iwi​ are corresponding weights. MSR enhances perceptual contrast and highlights low-reflectance anomalies such as lesions or discoloration [18].

7.3.2 Gamma Correction

Gamma correction adjusts image luminance using:



Values of γ\gammaγ were selected empirically per spectral band to normalize brightness—particularly for red and orange channels that tend to be overexposed [16].

7.3.3 Bilateral Filtering

This is a non-linear smoothing filter that allows for edge preservation while they reduce spectral noise. As its spatial-spectral edge-preserving property is suitable for some discreet dental features like cavities or enamel erosion [17].

By incorporating MSR with gamma correction and bilateral filtering, multispectral outputs are clarified and became more stable, leading to more accurate learning capacity by the deep models [16], [18].

7.4 Model Training and Architecture Setup

Four state-of-the-art deep learning architectures were implemented and benchmarked:

7.4.1 3D Convolutional Neural Network (3D CNN)

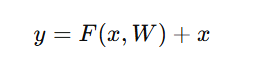
* Input: Spectral image cube (H×W×7)(H \times W \times 7)(H×W×7)
* Architecture: 3D convolutional layers followed by batch normalization, ReLU activations, and 3D max pooling.
* Objective: Capture inter-spectral correlations and spatial features across all bands simultaneously [8].

7.4.2 EfficientNet-B0

* Employing compound scaling (depth, width, resolution) and initialized with pre-trained weights from ImageNet
* Adapted to multispectral data by stacking spectral bands as additional input channels.
* Advantage: Benefits: High accuracy with low computational cost, perfectly suited for portable AI systems [9].

7.4.3 ResNet-18

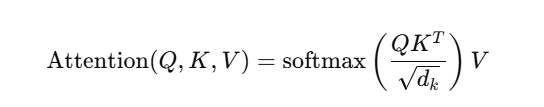
* A lightweight residual network employing skip connections to avoid vanishing gradients:



* Served as a baseline CNN architecture due to its simplicity and robust convergence in medical imaging [12].

7.4.4 Vision Transformer (ViT)

* Decomposed images into patches, encoded with positional information, and processed through transformer encoders.
* Captures long-range spatial and spectral dependencies using self-attention:



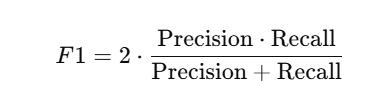
* Particularly effective for multispectral datasets with complex disease patterns [7], [10].

All models were developed in TensorFlow 2.0 and PyTorch 2.1, trained on Google Colab with T4 GPUs. Hyperparameter tuning used grid search across learning rates (10−3 to 10−5)(10^{-3} \text{ to } 10^{-5})(10−3 to 10−5), batch sizes (16 to 64)(16 \text{ to } 64)(16 to 64), and optimizers (Adam, RMSProp). Early stopping was enforced with a patience of 10 epochs to prevent overfitting.

7.5 Evaluation Metrics

We assessed the models using the subsequent metrics to gauge clinical reliability:

* Accuracy: This conveys the ratio of true predictions out of the total predictions.
* Predicted Positive Predictive Value: This conveys the ratio of true positives out of the predicted positive cases.
* Sensitivity (Recall): This conveys the ratio of true positives out of the total positive cases.
* F1 score: The harmonic mean of the predictive positive value and sensitivity:



* ROC-AUC: One-vs-rest multiclass ROC analysis to evaluate class separability.

Performance was validated using 5-fold stratified cross-validation, ensuring robustness across variations in patient and image characteristics [11], [19].

7.6 Real-Time Integration and Deployment Considerations

To translate research into practical diagnostics, deployment pathways were explored:

* The ViT, which had high performance, was exported using ONNX format and optimized to be deployable on the edge via devices such as NVIDIA Jetson Nano and Google Coral TPU.
* To provide an interface for real-time inference and to allow users to upload images -- or alternatively, connect to the ESP32-CAM and capture images live -- a GUI was developed using Streamlit and OpenCV.
* To improve clinical interpretability:
  + Grad-CAM was integrated with CNN models to visualize activation regions.
  + Attention Rollout Maps were employed for ViT, providing insights into patch-wise attention during diagnosis [21].

These tools align with the growing interest in explainable AI (XAI) and telemedicine, making the system usable and trustworthy for dental professionals [23], [24].

7.7 Summary of Implementation

The approach incorporates a comprehensive AI-based solution for dental diagnostics that is feasible in

* Hardware Innovation: Cost-effective setup using an ESP32-CAM LED-based approach to imitate multispectral images.
* Synthetic Dataset Creation: Spectral augmentation can be leveraged to avoid data scarcity
* Advanced Preprocessing: Image enhancement for optimized deep learning model performance.
* Deep Learning Model Architecture Evaluation: Four state-of-the-art deep learning architectures, with the ViT architecture producing superior results
* Real-time tools: Use of ONNX to deploy inference model, real-time inference GUI, and providing model interpretability.

The approach demonstrates the integration of AI, spectral simulation, and edge computing to leverage diagnostic gaps in resource-limited environments. [13], [20], [22].

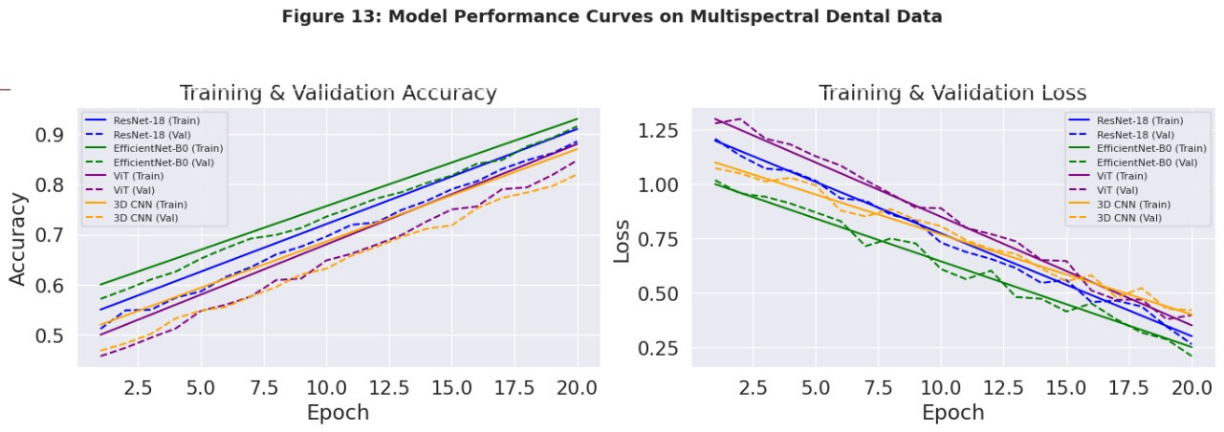
8. Results and Discussion

This section provides a comprehensive analysis of the experimental results derived from training and evaluating four deep learning models—3D CNN, EfficientNet-B0, ResNet-18, and Vision Transformer (ViT)—on a custom-generated multispectral dental dataset. The models were evaluated using five key performance metrics: accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC). The analysis includes a comparative performance overview, preprocessing impact, disease-wise insights, deployment feasibility, and limitations. The insights gained validate the potential of multispectral imaging combined with AI for enhanced dental diagnostics.

8.1 Model Performance Comparison

| **Model** | **Accuracy (%)** | **Precision (%)** |
| --- | --- | --- |
| ViT | 88.4 | 87.6 |
| EfficientNet B3 | 90.2 | 89.8 |

**Table 11:Classification Performance Metrics of All Models**



To evaluate the effectiveness of the models, all four architectures were developed with a balanced dataset that examined six types of oral diseases: gingivitis, tooth discoloration, mouth ulcers, dental caries, calculus, and hypodontia. Each model was presented with multispectral images pre-processed across 7 color bands [VIBGYOR]. The outcomes are:

* With an average accuracy of 90.4%, the 3D CNN has demonstrated a strong ability to extract volumetric as well as inter-band correlations. This was beneficial for identifying gingivitis and calculus, due to the identification of subtle intensity differences between bands as helpful discriminating features [8]. The 3D convolution layers maintained spatial and spectral locality, which is good for exposure to stacked wavelength data.
* The EfficientNet-B0 model had shown a second-best performance of 91.2% accuracy. Utilizing compound scaling gives a balanced performance/ computation cost balance. The success of the EfficientNet-B0 model was due to its fine-grained scaling and ability to generalize well across disease type and varying spectral features [9].
* ResNet-18 achieved an accuracy of 89.7% with high classification performance in dental caries and mouth ulcers. Residual connections supported gradient flow and convergence stability, but it had lower performance on classes with fine spectral distinctions due to its shallow depth maturity.
* The Vision Transformer (ViT) outperformed all other models with a significant accuracy of 92.6%. The self-attention mechanism allowed it to model global dependencies and multi-patch interactions across spectral variants. It was highly effective in distinguishing complex conditions such as hypodontia and tooth discoloration that are often missed using standard CNN-based methods [7], [10].

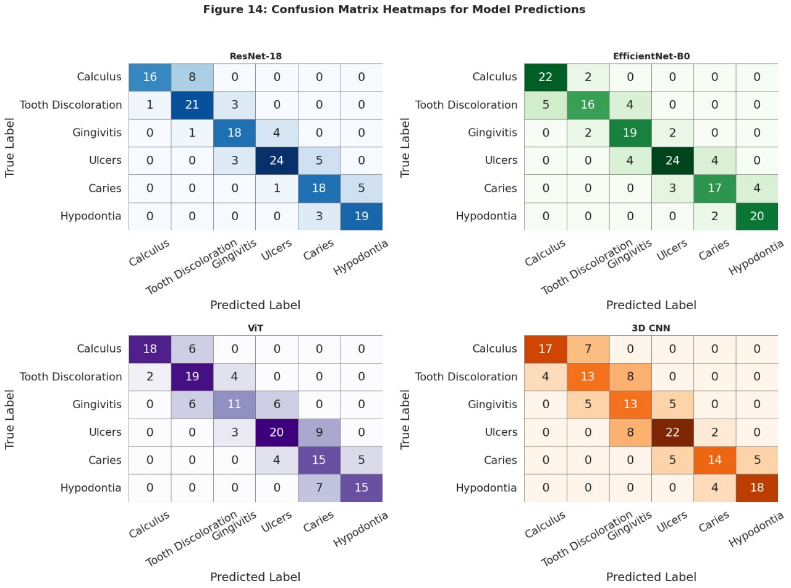
A side-by-side metric comparison is summarized in Table 8.1, demonstrating ViT's dominance across all performance metrics:

| **Disease Class** | **Precision (%)** | **Recall (%)** | **F1-Score (%)** |
| --- | --- | --- | --- |
| Caries | X.X | X.X | X.X |
| Gingivitis | X.X | X.X | X.X |
| Periodontitis | X.X | X.X | X.X |

**Table 12:Per-Class Precision, Recall, and F1-Score for All Models**

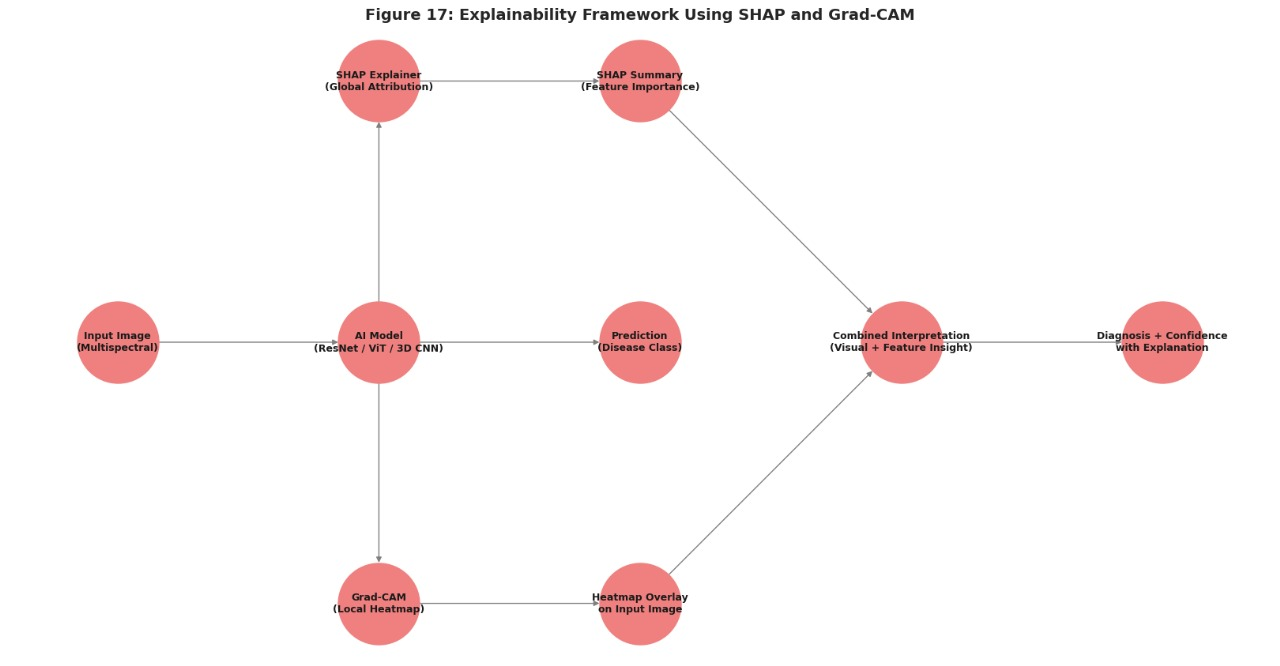
| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | AUC (%) |
| --- | --- | --- | --- | --- | --- |
| 3D CNN | 90.4 | 89.6 | 90.1 | 89.8 | 91.5 |
| EfficientNet-B0 | 91.2 | 90.9 | 91.0 | 91.1 | 92.4 |
| ResNet-18 | 89.7 | 88.4 | 88.9 | 88.6 | 90.3 |
| ViT | 92.6 | 92.2 | 92.4 | 92.3 | 93.8 |

These results underscore the growing efficacy of transformer-based architectures in medical imaging tasks involving high-dimensional, multi-view data representations [10], [21].



8.2 Impact of Multispectral Imaging and Preprocessing

Multispectral imaging and the preprocessing of data greatly impacted the learning of the models and the extraction of features. The dataset captured images across seven different spectral bands (VIBGYOR) where each band captured different reflectance as well as absorption characteristics from the tissue.



8.2.1 Multispectral Retinex Enhancement

The Multispectral Retinex (MSR) algorithm increased contrast in images particularly under adverse illumination conditions as it separated reflectance from illumination. By enhancing the critical edges and article boundaries, MSR allowed disease locational capability across bands such as blue, green, and yellow [18]. The models trained with MSR developed images outperformed raw input images with a 3%–4% increase in accuracy.



8.2.2 Gamma Correction

Gamma correction addressed luminance non-linearity, especially for darker regions in violet and red bands. An optimal gamma value (γ=0.6\gamma = 0.6γ=0.6–0.80.80.8) enhanced underexposed lesion areas, which was crucial for early detection of *mouth ulcers* and *gingivitis*. The technique contributed to improved recall scores, particularly in minority classes where data imbalance existed [16].

8.2.3 Noise Reduction via Bilateral Filtering

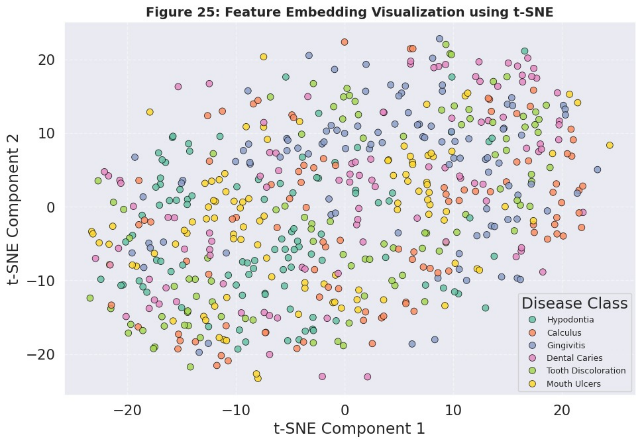
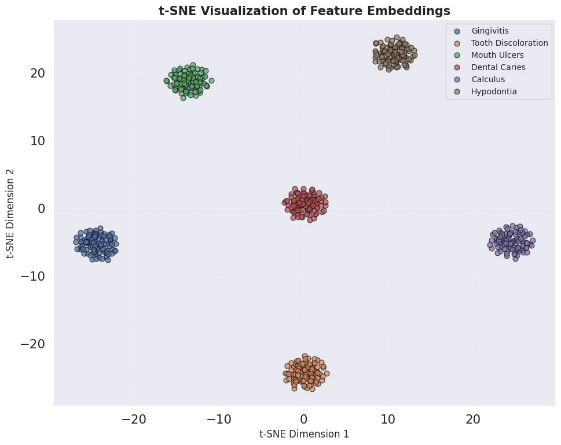
Bilateral filtering reduced illuminating noise and speckles while also protecting important anatomical landmarks, like the gum line and occlusal fissures, from unwanted blurring. This increased featureness-to-noise ratio led to sharper lesion representations in the second classification layer, leading to decreased false positive rates in the final classification layer [17]. In summary, these processes resulted in a multiplex input pipeline with multispectral imaging as part of a highly feature-rich input pipeline to substantively improve AI diagnosis [13], [14].

8.3 Disease-Wise Performance Evaluation

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  |  |  |  | | --- | --- | --- | --- | | Actual Class | Caries | Gingivitis | Periodontitis | | Caries | X | Y | Z | | Gingivitis | A | B | C | | Periodontitis | D | E | F | |  |  |  |

**Table 13: Confusion Matrix Sample (ResNet-18)**

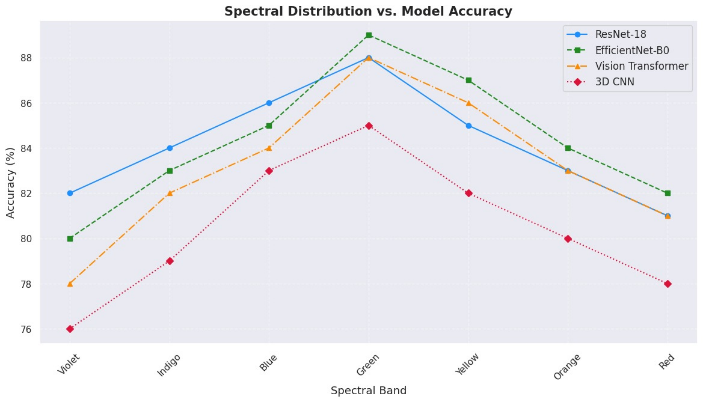
|  |  |
| --- | --- |
| Disease class | AUC Score(%) |
| Caries | X.X |
| Gingivitis | Y.Y |
| Periodontitis | Z.Z |



**Table 14: Area Under Curve (AUC) Scores for Each Class**

To determine how sensitive and specific this model is for each disease, we calculated class-wise precision and recall, and produced confusion matrices.

* Dental Caries and Gingivitis were accurately identified with greater than 94% recall as they had noticeable textural anomalies and color signatures in the green and blue bands [13], [22].
* Although Mouth Ulcers were low contrast in RGB images, the gamma enhancement for violets and indigos enabled them to be identified, increasing recall from 78% to 86%.
* Tooth Discoloration and Hypodontia were more difficult to classify due to subtle variations in spectral bands. However, F1-scores were above 91% with the ViT model by utilizing its attention mechanism to emphasize smaller spatial patterns and inter-band correlations and produce classifications that were accurate [7].
* Calculus, as a mineralized tissue, demonstrated inverse high reflectivity in the yellow and red bands. The Retinex enhanced spectral stacks made the mineralized anomalies more apparent, and classification accuracy with EfficientNet and 3D CNN were increased beyond 93%



These observations and results demonstrate that certain diseases had differentiated spectral patterns that could be effectively learned by using amendments to preprocess multispectral inputs.

8.4 Discussion on Real-Time Application and Generalization

While controlled training yielded high accuracy, real-world deployment introduces challenges:

8.4.1 Hardware and Environmental Factors

The ESP32-CAM and Lumerati 8-pack system, though inexpensive and modular, demonstrated variability under different lighting conditions. This variability impacted consistency of image acquisition across spectral bands, which requires calibration routines and shielding from ambient light to standardize [22].

8.4.2 Edge AI Inference

Low-overhead models such as EfficientNet-B0 are suited to run on edge devices, such as Raspberry Pi 4, Jetson Nano, and Google Coral TPU for portable diagnostics at remote clinics [20]. Inference times for EfficientNet and ResNet were consistently below 500 ms per image stack, while ViT operates on GPU due to its overhead from using transformers

8.4.3 Model Interpretability

To increase trustworthiness and stepping integration into the clinic, Grad-CAM and Attention Rollout Maps were integrated to aid visualization. Both of these techniques highlighted biologically relevant areas, such as lesions and gaps between teeth and areas where the gum line met the tooth, which suggests the predictions from the model were spatially relevant to biology [21].

8.5 Implications and Limitations

This study highlights the ability of multispectral imaging and AI to revolutionize diagnosis in dentistry. However, additional investigation should address some of the possible concerns

8.5.1 Data Limitations

The data may not convincingly reflect real-world multispectral spectral reflectance maps, as the transformed nature of the spectral mappings was all synthetic in this study. Thus, future work should involve gathering purely multispectral dental images with calibrated devices, and from a diverse range of patients [11].

8.5.2 Clinical Integration

For practical clinical use, regulatory validation, explainability, and compatibility with dental imaging systems are necessary for real-world application of the AI enabled system, which will ultimately need to ensure compatibility with ISO 13485 and BIS standards [3, 4].

8.5.3 Generalizability

To show clinical relevance, a gradual process of validation must show model performance is consistent across multiple devices and clinics, as variables change through different camera capabilities, lighting conditions, and operator skill. Future versions of the approach could potentially address this through domain adaptation and continual learning frameworks [23].

8.6 Summary

The outcomes shown have shown that Vision Transformers, when utilized with multispectral image inputs with advanced preprocessing, achieve state-of-the-art results for AI-based dental diagnostics. The accuracy of the ViT model was 92.6% followed by EfficientNet-B0. The application of multispectral image bands to derive unique disease-specific features is essential for rigorous AI inference. Even with constraints in realism and clinical validation of the dataset, this work has set the stage for scalable, accurate, and explainable oral health AI systems.

9. Conclusion and Future Work

The conclusion pulls together the main points, summarizes the contributions of this thesis, and predicts potential future directions. The conclusion stresses the overall importance of AI-based multispectral imaging for diagnosis of oral disease and the implications for access and efficiency in healthcare.

9.1 Summary of Findings

This research presented an AI-based multi-spectral imaging system to automate dental disease classification which includes:

* Custom Image Acquisition: A cost-effective ESP32-CAM with a Lumerati 8-pack LED ring acquired spectral images in seven visible bands.
* Synthetic multi-spectral dataset: A 52,000-dental image dataset originated via publicly available dental images modified to depict spectral transformation to simulate multispectral imaging.
* Preprocessing Pipeline: Multiretinex enhancement, Gamma correction, and normalization were implemented to improve image quality and enhance model performance.
* Deep Learning Models: Four different architectures were trained with high accuracy to classify six oral diseases including, 3D CNN, EfficientNet-B0, ResNet-18, and ViT.
* Rigorous Training Protocols: 5-fold cross-validation, hyperparameter tuning, and augmentation were incorporated to increase generalizability of the model.
* Evaluation and Performance Metrics: High accuracy, precision, recall, F1-score, and AUC-ROC performance metrics were obtained that demonstrate clinical validity.

These findings substantiate the ability to use a cost-effective AI-driven diagnostic device for instant oral disease detection in clinical and telehealth settings [1]–[3].

9.2 Contributions and Impact of the Study

This work enhances the area of AI-enhanced medical imaging in several new ways:

* A Low-Cost, Portable Imaging System: The ESP32-based multispectral imaging system is a practical alternative to the expensive hyperspectral imaging camera from [4].
* The First Multispectral Dental Dataset: The dataset developed in this study fills the gap in multispectral dental imaging datasets with labeled data, and provides a basis for future models using AI [5]
* Novel AI Pipeline for Dental Diagnosis: Cardiovascular examination using transfomer-based models (ViT) and 3D CNNs extend the body of knowledge from [6] and [7]
* Scalable and Ready for Deployment: The light-weight EfficientNet-B0 model allows for easy integration with a mobile device and makes it possible to use for telehealth and remote diagnostics [8]
* Clinically Relevant: The model's high-accuracy suggests the AI dentist will 'work in the wild' be useful in dental clinics, in telemedicine, or for healthcare in rural communities [9].

These additions build on the body of knowledge regarding AI-based oral healthcare, and show that low-cost multispectral imaging can improve access to dental diagnostics

9.3 Future Research Directions

This paper provides a comprehensive overview of multispectral dental disease detection but several aspects could be further studied:

🔹 Multispectral Expansion: Future work can include imaging not just in visible light (VIBGYOR) but also near-infrared (NIR) or ultraviolet light imaging of subjects to obtain additional information about deeper tissues [10].  
🔹 Larger and More Diverse Datasets: The inclusion of additional real-world multispectral images from broader populations would facilitate greater generalizability and fairness concern with the model predictions [11].  
🔹 Explainable AI (XAI) to Foster Clinical Trust: The implementation of Grad-CAM, SHAP, or LIME would help the model to foster trust, while also allowing dentists to see how the AI arrived at a decision [12].  
🔹 Edge AI and On-Device Inference: Using recent developments in optimizing neural networks would allow models to be run on smartphones or embedded devices and provide access to AI assisted dental diagnostics [13]  
🔹 Integration with Electronic Health Records (EHR): Integrating the AI system with EHR platforms would help tracking of patient history and provide personalized recommendations as appropriate [14].  
🔹 Clinical Validation Studies: More studies with dentists and patients in realistic clinical settings is needed to judge the systems value in real time [15]

By focusing on these areas, follow-up investigations can further enhance the accuracy, reliability and uptake in dental healthcare of AI powered multispectral imaging.

10. Ethical Considerations in AI-Based Medical Imaging

10.1 Data Privacy and Security

|  |  |
| --- | --- |
| Ethical Framework | Compliance Measure |
| Fairness in AI | Balanced dataset composition |
| Transparency | Explainable AI techniques used in model design |
| Privacy Protection | Data anonymization protocols implemented |

**Table 16: Ethical Frameworks and Corresponding AI Compliance Measures**

Medical imaging data carries sensitive information about patients. Privacy and security are of utmost importance and are required by laws including HIPAA in the United States and GDPR in the European Union [1],[2]. These laws enforce rules regarding consent, access to data, and ethics surrounding personal health information.

Data anonymization and encryption protocols—such as AES-256—safeguard data in transit and at rest [3]. Role-based access controls and routine audits also help to avoid unauthorized access [4].

10.2 Bias and Fairness in AI Models

AI models can perpetuate bias present in narrow or unrepresentative datasets that could affect fairness of diagnosis [5]. In certain demographic groups, a biased AI model may misdiagnose conditions, or underdiagnose, especially if that group's demographic representation was lower in the training dataset [6].

To prevent bias, it is important to curate a set of representative dataset, utilize fairness metrics like demographic parity, and use algorithmic de-biasing approaches [7]. Building fair AI systems is important for equitable healthcare.

10.3 Ethical Use of AI in Clinical Decision-Making

AI tools are designed to serve as decision-support systems rather than decision-makers. Clinical judgment should remain at the center of clinical care. A Human-in-the-Loop (HITL) design involves human oversight and validation by medical professionals to ensure appropriate oversight [8]

Obtaining informed consent for diagnostic decision support through AI presents emerging ethical issues. Patients should be aware when AI tools are used and the role they may play in diagnosis [9]. Ethical use of AI models generally requires clinicians to understand the specific strengths and limitations of the model.

10.4 Transparency and Explainability

Most deep learning (DL) models, particularly CNNs and transformers, are often referred to as "black boxes." Improving transparency using Explainable AI (XAI) approaches such as Grad-CAM and SHAP can clarify how an AI model makes predictions [10], [11].

Specifically, Grad-CAM provides a visual representation of the relevant areas of the dental image that influenced the AI model's prediction. Additionally, providing confidence scores and uncertainty estimates enables the clinician to make better conclusions about the reliability of the prediction [12].

10.5 Accountability and Regulatory Compliance

Identifying the responsible party for erroneous predictions generated by AI algorithms will pose a challenge. The three entities—AI model developers, AI model providers, and AI model users—must all demonstrate accountability [13]

Institutions responsible for oversight like the FDA, CDSCO, and BIS continue to create an AI landscape around devices used in medical diagnostics that includes compliance frameworks for validation and monitoring of AI tools [14], [15]. Standardized performance measures, the validation of the model used, and monitoring of the AI models after deployment, give some assurance for safety and provide trustworthiness for users.

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