CHAPTER - 1

INTRODUCTION

1.1 OVERVIEW

Oral cancer is a significant public health concern affecting millions of people worldwide. It is one of the most common cancers, especially in developing countries where risk factors such as tobacco use, excessive alcohol consumption, and poor oral hygiene are prevalent. A major challenge in addressing oral cancer is the delay in diagnosis, which results in late-stage detection and consequently lower survival rates. According to the World Health Organization (WHO), early detection of cancer significantly improves the chances of successful treatment. However, due to a lack of awareness, limited access to specialized medical care, and the shortage of trained oncologists in many regions, early diagnosis remains a challenge.

AI models can now analyze medical images with high accuracy, sometimes matching or even surpassing human experts. Deep learning, particularly convolutional neural networks (CNNs), has proven highly effective in tasks such as image classification, object detection, and segmentation. This project taps into the power of deep learning to address the problem of oral cancer detection through image classification.

The project involves building an AI-powered system capable of classifying oral cavity images into three clinically significant categories: Benign, Healthy, and OPMD (Oral Potentially Malignant Disorders). The solution is built on top of MobileNetV3, a highly efficient and lightweight CNN architecture designed to work well even on devices with limited computational resources. This makes the model suitable for real-world deployment, especially in areas with minimal access to advanced healthcare infrastructure.

1.2 ABOUT THE PROJECT

The goal of this project is to assist in the early detection and classification of oral cancer using advanced deep learning techniques. By leveraging image classification capabilities of CNNs, the system can automatically analyze and interpret oral images, distinguishing between normal tissues and those that exhibit signs of malignancy or pre-malignancy. The motivation behind the project stems from the need to provide accessible and cost-effective diagnostic tools that can aid healthcare professionals and support screening programs, especially in rural and underserved regions.

At the core of this system is the MobileNetV3 architecture. This model is specifically optimized for speed and performance, making it ideal for mobile and embedded applications. It strikes a balance between computational efficiency and classification accuracy, enabling it to perform well on image classification tasks without requiring high-end hardware. The model is trained on a curated dataset of oral cavity images and is fine-tuned to recognize the subtle differences between the three target classes.

In addition to the model itself, a user-friendly web-based interface is developed using the Flask web framework. This allows users, such as clinicians, healthcare workers, or even individuals, to upload an image of the oral cavity and receive an instant prediction. The interface is designed to be intuitive and responsive, making it accessible even to users with limited technical expertise. The seamless integration of the model with the web application ensures that the system is not just a theoretical prototype but a practical solution ready for real-world use.

1.3 KEY FEATURES OF THE PROJECT

- **Efficient Deep Learning Model:** Utilizes MobileNetV3, a lightweight yet powerful CNN architecture suitable for deployment on mobile and edge devices.

- **Multi-Class Classification:** Capable of categorizing oral images into three critical classes: Benign, Healthy, and OPMD.
- **Web Interface Integration:** A Flask-based web application enables easy interaction with the model through a graphical user interface.
- **Data Augmentation and Preprocessing:** Techniques such as image resizing, rotation, flipping, and color jittering are used to improve model generalization.
- **Scalable and Deployable:** The system is optimized for deployment in low-resource settings and can be scaled or adapted for broader use.
- **Supports Early Detection:** Helps in the early identification of potentially malignant oral lesions, improving chances of successful treatment.
- **User-Centric Design:** The application is designed with usability in mind, ensuring that it can be operated by both medical professionals and laypersons.

1.4 BENEFITS OF THE PROJECT

The proposed system offers a range of benefits to both healthcare providers and patients. First and foremost, it supports early detection of oral cancer, which is crucial for effective treatment and improved survival rates. By automating the diagnostic process, it reduces the dependency on specialist expertise and helps in standardizing diagnostic results.

The project also enhances accessibility to diagnostic tools. In many rural and underdeveloped regions, access to oncologists or specialized imaging equipment is limited. A lightweight, AI-powered solution that can run on standard computing devices or mobile platforms provides a cost-effective alternative. It can be used in remote health camps, local clinics, and mobile screening units.

Additionally, the system reduces diagnostic time. Instead of waiting days for expert analysis, users can get instant predictions. This is particularly useful in time-sensitive cases where early intervention can make a significant difference. The model's integration with a web-based interface ensures that it is easy to use and widely deployable.

From a research and development perspective, this project contributes to the field of AI in healthcare by showcasing how modern machine learning architectures can be applied to real-world medical problems. It also provides a foundation for future projects, including the expansion of classification capabilities to include more types of oral diseases and integration with electronic health records (EHR) systems.

1.5 SCOPE OF THE PROJECT

The scope of this project encompasses the development, training, evaluation, and deployment of an AI-based image classification model tailored for oral cancer detection. It includes the design and implementation of a CNN model (MobileNetV3), the collection and preprocessing of image data, and the construction of a web interface for real-time prediction.

While the current focus is on classifying three types of oral conditions, the system can be extended to cover a broader range of oral diseases. Future enhancements could involve integrating the system with cloud platforms for centralized data storage and remote access, or connecting it with health information systems for automated patient record updates.

The project is intended for real-world application, particularly in regions where medical resources are scarce. It demonstrates how cutting-edge AI technologies can be harnessed to create practical tools that address pressing healthcare challenges. Through this initiative, the groundwork is laid for more comprehensive, intelligent, and inclusive medical diagnostic systems.

CHAPTER – 2

LITERATURE SURVEY

2.1 INTRODUCTION

The advent of artificial intelligence (AI) and deep learning has revolutionized medical image analysis, enabling significant strides in early disease detection and screening. Oral cancer, particularly Oral Squamous Cell Carcinoma (OSCC), stands to benefit considerably from these advances, as timely diagnosis dramatically affects patient outcomes. In recent years, convolutional neural networks (CNNs) have been the architecture of choice for interpreting complex visual patterns in medical images. However, many early studies relied solely on image data, overlooking complementary clinical context. More recent work has begun to address this gap through multimodal approaches—fusing image features with patient metadata to more closely emulate clinician decision-making. At the same time, lightweight architectures such as MobileNetV2/V3 [1,2] and EfficientNet variants [3] have demonstrated that high accuracy can be achieved with reduced computational cost, a critical requirement for real-world deployment in low-resource settings. Transformer-based models (e.g., Vision Transformer, ViT) and hybrid CNN–transformer networks further promise improved feature representation but remain data-hungry and compute-intensive [4]. This survey reviews the spectrum of methodologies—from pure CNN backbones and transfer learning on histopathology images to multimodal pipelines and emerging transformer-based frameworks—and identifies persistent challenges that motivate our proposed system.

2.2 LITERATURE REVIEW

Devindiet al. (2024)

Devindi and colleagues introduced a multimodal deep-learning pipeline that integrates smartphone-captured oral cavity images with patient metadata (age, sex, habits) for early OSCC detection [5]. A modified U-Net segmented the oral region to remove background artifacts, and six CNN backbones (DenseNet-121, Inception_v3, ResNet-50, HRNet-W18-C, MixNet-S, MobileNetV3-Large) were compared. MobileNetV3-Large emerged best, achieving 81% accuracy, 79% precision, and an MCC of 0.57. They demonstrated that weighted loss functions outperformed data-level augmentation in handling class imbalance, and early feature-level fusion consistently beat late fusion and image-only baselines.

Lin et al. (2021)

Lin et al. explored dual-modality screening by combining RGB smartphone images and autofluorescence (AFI) using transfer learning on HRNet and ResNet architectures [6]. Their model attained over 85% sensitivity and 82% specificity on community-acquired data. This work underscored the viability of inexpensive handheld devices but highlighted challenges in standardizing illumination and imaging conditions.

Uthoff et al. (2018)

Uthoff et al. developed a mobile fluorescence imaging attachment for smartphones and applied a pretrained VGG-M network to classify suspicious versus non-suspicious lesions [7]. On 170 image pairs, they achieved sensitivity and specificity above 80%, validating point-of-care fluorescence screening. However, reliance on AFI limited generalizability where such attachments were unavailable.

Amin et al. (2021)

Amin and colleagues employed transfer learning on concatenated outputs of ResNet-50 and EfficientNet-B0 to classify histopathology patches as OSCC or normal [8]. Their ensemble achieved >90% accuracy, demonstrating that biopsy-level imaging yields very high diagnostic precision. The drawback remains invasiveness and the need for pathology workflows.

Zhang et al. (2019)

Zhang et al. introduced an attention-residual learning framework for skin lesion classification, combining residual blocks with channel-wise attention [9]. On the ISIC dataset, they reported an AUC of 0.92. This architecture inspires similar attention mechanisms to focus on salient lesion regions in oral images.

Howard et al. (2019) and **Sandler et al. (2018)**

Howard et al. and Sandler et al. developed MobileNetV3 and MobileNetV2, respectively, introducing inverted residual blocks and lightweight architectures [1,2]. MobileNetV3-Large achieves a favorable accuracy–latency trade-off on ImageNet, making it ideal for on-device oral lesion screening.

Dosovitskiy et al. (2021)

Dosovitskiy et al. demonstrated that pure Vision Transformer (ViT) models can match CNN performance when pretrained on massive datasets [4]. However, the data and compute requirements currently limit adoption for smaller medical image collections.

2.3 CONCLUSION

Across the reviewed literature, two clear trends emerge: (1) multimodal fusion of imaging and metadata enhances diagnostic accuracy and clinical relevance, and (2) lightweight CNN architectures like MobileNetV2/V3 and EfficientNet variants offer practical performance for real-world deployment. While transformer-based models hold promise, their resource demands and scarcity of large-scale oral image datasets temper their immediate applicability. Our project builds directly upon Devindi et al.'s multimodal U-Net + MobileNetV3 pipeline, incorporating weighted loss training and early fusion, and seeks to further refine segmentation, metadata encoding, and deployability via a responsive web interface. By balancing model efficiency, data diversity, and clinical context, we aim to deliver a robust tool for early oral cancer screening in resource-limited settings.

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CHAPTER - 3

PROJECT DESCRIPTION

3.1 OBJECTIVE OF THE PROJECT

Oral cancer remains a leading cause of morbidity and mortality worldwide, with survival rates strongly tied to the stage at which it is detected. Traditional diagnostic workflows—visual oral examination followed by biopsy—are highly effective when conducted early, but in practice suffer from delays in referral, uneven access to specialists, and variability in clinical interpretation. The primary objective of this project is therefore to develop an AI-powered screening tool that can rapidly and non–invasively classify images of the oral cavity into three clinically meaningful categories:

1. **Healthy** (no visible pathology),
2. **Benign** (non-malignant lesions such as aphthous ulcers), and
3. **OPMD** (Oral Potentially Malignant Disorders), which carry elevated risk of progression to cancer.

By harnessing a state-of-the-art, lightweight convolutional neural network—MobileNetV3—we aim to minimize both computational footprint and inference latency, enabling deployment on standard laptops, tablets, or even smartphones. This tool is not intended to replace biopsy or pathological confirmation but to function as a pre-screening aid, flagging suspicious cases for expedited clinical follow-up.

In pursuit of this goal, we define the following sub-objectives:

- **Data footprint optimization**: Balance and augment the dataset so that each class (Healthy, Benign, OPMD) has roughly equal representation, thereby preventing training bias.

- **Model efficiency**: Fine-tune MobileNetV3 through transfer learning, optimizing only the final classification layers, and evaluate against baseline architectures.
- **User accessibility**: Wrap the trained model within a Flask web application, providing a simple upload interface and clear, actionable output.
- **Performance validation**: Assess model performance using accuracy, precision, recall, F1-score, confusion matrix analyses, and—where feasible—clinician review of edge cases.

Ultimately, we seek to demonstrate a deployable, user-centric pipeline that can be integrated into routine dental or community screening programs, reducing diagnostic delays and improving patient outcomes.

3.2 EXISTING SYSTEM

3.2.1 Conventional Diagnostic Workflow

The current standard for oral cancer detection begins with a Conventional Oral Examination (COE). In COE, a clinician visually inspects the tongue, floor of mouth, buccal mucosa, gingiva, and palate for abnormal lesions—white patches (leukoplakia), red patches (erythroplakia), or ulcerative growths. Suspicious findings prompt a biopsy, followed by histopathological analysis to confirm malignancy. While gold-standard accurate, this process is:

- **Time-intensive**: Multiple patient visits—screening, biopsy, and follow-up.
- **Resource-heavy**: Requires dental specialists, pathologists, and laboratory infrastructure.
- **Subjective**: Sensitivity and specificity vary greatly between practitioners, leading to inter-observer variability.

3.2.2 Digital and AI-Assisted Approaches

Over the past decade, several adjunct technologies have emerged:

- **Autofluorescence & Toluidine Blue Staining**: Specialized lights or dyes highlight dysplastic tissue.
- **Intraoral Cameras & High-Resolution Imaging**: Offer improved visualization but still rely on human interpretation.
- **Machine Learning on Histopathology**: Deep CNNs classify digitized biopsy slides with high accuracy, but only post-biopsy.
- **Smartphone-Based Screening**: Early work has shown promise in classifying images captured by phone cameras, yet many models remain monomodal (image-only) and unbalanced.

These systems demonstrate the feasibility of computer-aided diagnosis but suffer from key shortcomings:

1. **Equipment Cost & Complexity**: Autofluorescence devices and staining protocols add expense and training overhead.
2. **Limited Accessibility**: Most solutions are confined to tertiary care centers.
3. **Narrow Scope**: Many AI models address only “cancer” vs. “non-cancer” without distinguishing benign lesions or OPMDs.
4. **Deployment Barriers**: Large neural networks (ResNet-50, Inception) demand GPU-class hardware, hindering mobile or web deployment.

3.2.3 Gaps and Motivation

Our survey of the literature clearly shows:

- A need for lightweight architectures that retain high accuracy—MobileNetV3 fills this niche.

- A desire for multiclass classification (Healthy/Benign/OPMD), rather than binary.
- The importance of a balanced, augmented dataset to avoid bias.
- The value of an end-to-end deployable solution bridging image capture, inference, and user feedback.

3.3 PROPOSED SOLUTION

To address these gaps, we propose a three-tiered pipeline:

1. Data Preparation & Augmentation
2. Model Training & Optimization
3. Web Deployment & User Interface

3.3.1 Data Preparation and Augmentation

The foundation of any machine learning model lies in the quality and organization of its dataset. In this project, the dataset is carefully organized into three primary classes: Benign, Healthy, and OPMD, with each class containing 730 images. To ensure effective training and evaluation, the dataset is split into three subsets: 80% for training, 10% for validation, and 10% for testing. This class-wise distribution helps preserve the integrity of each class throughout all phases of model development.

In order to prevent model overfitting and improve generalization, several data augmentation techniques are applied to the training set. These include random horizontal flips, rotations, and color jittering. Additionally, lightweight augmentation strategies like TrivialAugment are applied particularly to the minority classes to further enrich the diversity of samples. Preprocessing steps like resizing, normalization, and format conversion are used to ensure that the input images are compatible with the MobileNetV3 model architecture. To maintain balance in class representation during training, a weighted sampling strategy is used, ensuring that all three classes contribute equally to the learning process despite any minor residual imbalance.

3.3.2 Model Training and Optimization

The core of the proposed solution is the MobileNetV3-Large architecture, chosen for its efficiency, compact size, and proven performance on image classification tasks. The model is initialized with pre-trained weights from ImageNet, and then fine-tuned on the oral image dataset through a process known as transfer learning. In this process, the early layers of the model (which capture generic visual features) are frozen, while the final classification layer is replaced and trained specifically to recognize the three target classes in this project.

To optimize performance, the training process uses the Adam optimizer with a carefully chosen learning rate, and the cross-entropy loss function is modified with class-specific weights to counteract any imbalance in the dataset. The model is trained over multiple epochs, with accuracy and loss monitored on both training and validation sets. Early stopping and learning rate scheduling techniques are used to prevent overfitting and enhance convergence. Throughout the training, key performance metrics such as accuracy, precision, recall, and F1-score are calculated to assess the model's classification ability. Visualizations of training and validation loss/accuracy curves are also generated to track progress and guide adjustments.

3.3.3 Web Deployment and Interface

To enhance accessibility and usability, the trained model is integrated into a web-based application using the Flask framework. This application provides a simple and user-friendly interface that allows users to upload oral cavity images and receive real-time predictions. The backend receives the uploaded image, processes it using the same transformations used during training, and passes it to the MobileNetV3 model for inference. The model's output is then converted into a human-readable prediction along with a confidence score, which is sent back to the user.

The frontend is designed with simplicity and responsiveness in mind. Users interact with a single-page layout featuring a custom-styled file upload button and a "Predict" option. Once an image is submitted, the application displays the predicted class (Benign, Healthy, or OPMD) along with a visual confidence indicator. This system demonstrates how AI models can be effectively deployed in real-world settings, allowing for non-invasive, rapid, and accessible oral cancer screening. The entire pipeline, from model training to deployment, is optimized to run efficiently even on devices with limited resources, making it suitable for use in clinics, dental camps, and rural health centers.

3.4 SUMMARY

This chapter outlined the foundation and direction of the project by clearly defining its objective, analyzing the limitations of existing systems, and proposing a novel AI-driven solution. The main goal of the project is to develop an efficient, accurate, and deployable system for early detection of oral cancer using deep learning techniques, particularly MobileNetV3.

The discussion on existing systems revealed that traditional diagnostic methods are often time-consuming, cost-intensive, and heavily reliant on specialist availability, which limits their accessibility—especially in rural and under-resourced areas. While some early AI systems have attempted to address this gap, most suffer from model complexity, limited real-world usability, or lack of deployment frameworks.

To overcome these challenges, a lightweight and optimized MobileNetV3-based solution was proposed. The system integrates image classification with a responsive web interface, allowing users to upload oral images, receive predictions instantly, and generate diagnostic reports. It is designed to be scalable, user-friendly, and capable of functioning on edge devices or online platforms, making it suitable for early screening in both clinical and non-clinical environments.

Overall, this chapter set the stage for the system's development by presenting a clear rationale for innovation and demonstrating how the proposed approach aims to improve oral healthcare accessibility and diagnostic efficiency.

CHAPTER - 4

SYSTEM DESIGN

4.1 ARCHITECTURE DIAGRAM

The architecture of the proposed oral cancer classification system is centered around the MobileNetV3-Large model, which is widely recognized for its lightweight structure and efficiency in resource-constrained environments. The design of this architecture enables accurate classification while ensuring quick response time and reduced computational requirements—making it suitable for real-time diagnostic support in clinical and remote settings.

As shown in the architecture diagram, the input to the model is a preprocessed RGB image of the oral cavity, resized to a standard resolution of $224 \times 224 \times 3$. The image is then passed through five core stages, consisting of a series of depthwise separable convolutions and inverted residual blocks, which are key design features of MobileNetV3. These blocks efficiently capture both low-level and high-level features while maintaining a compact model size.

In the later layers of the network, adaptive average pooling is applied to reduce the spatial dimensions and consolidate the learned features. Following this, a 1×1 point-wise convolution is used to transform the feature map into a low-dimensional representation. This output is then passed through a final classification layer, which has been modified through transfer learning to predict one of three classes: Benign, Healthy, or OPMD (Oral Potentially Malignant Disorder).

The model has been fine-tuned using a transfer learning approach, where the earlier convolutional layers (responsible for general feature extraction) are retained, and only the later layers are updated using the oral cancer dataset. This significantly reduces training time and improves model convergence, particularly when training on a limited dataset.

Finally, the output of the model is integrated with a web-based interface, allowing users to upload oral images and receive classification results in real time. This architecture ensures a streamlined pipeline from input to prediction, offering a practical and accessible solution for AI-assisted oral cancer screening.

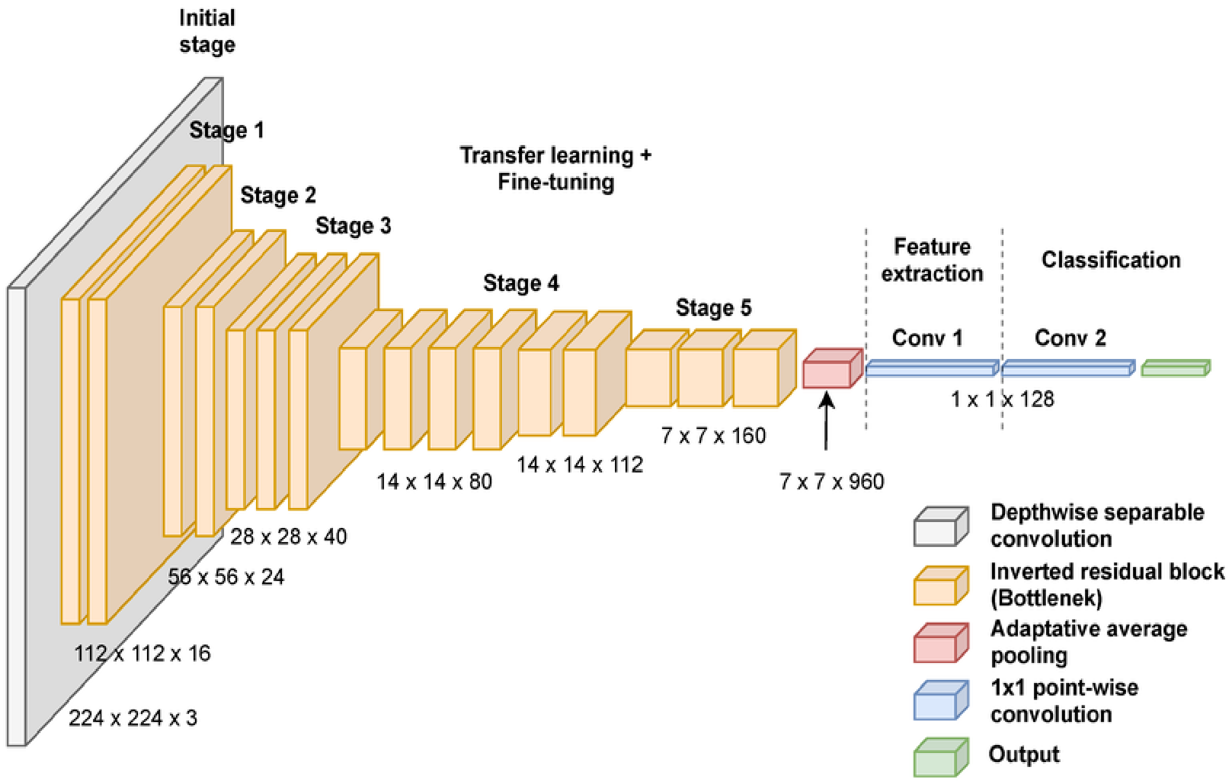

Fig 4.1.1 MOBILEV3NET FEATURE EXTRACTION DIAGRAM

https://www.researchgate.net/figure/The-architecture-of-MobileNetV3-used-for-feature-extraction_fig2_355479117

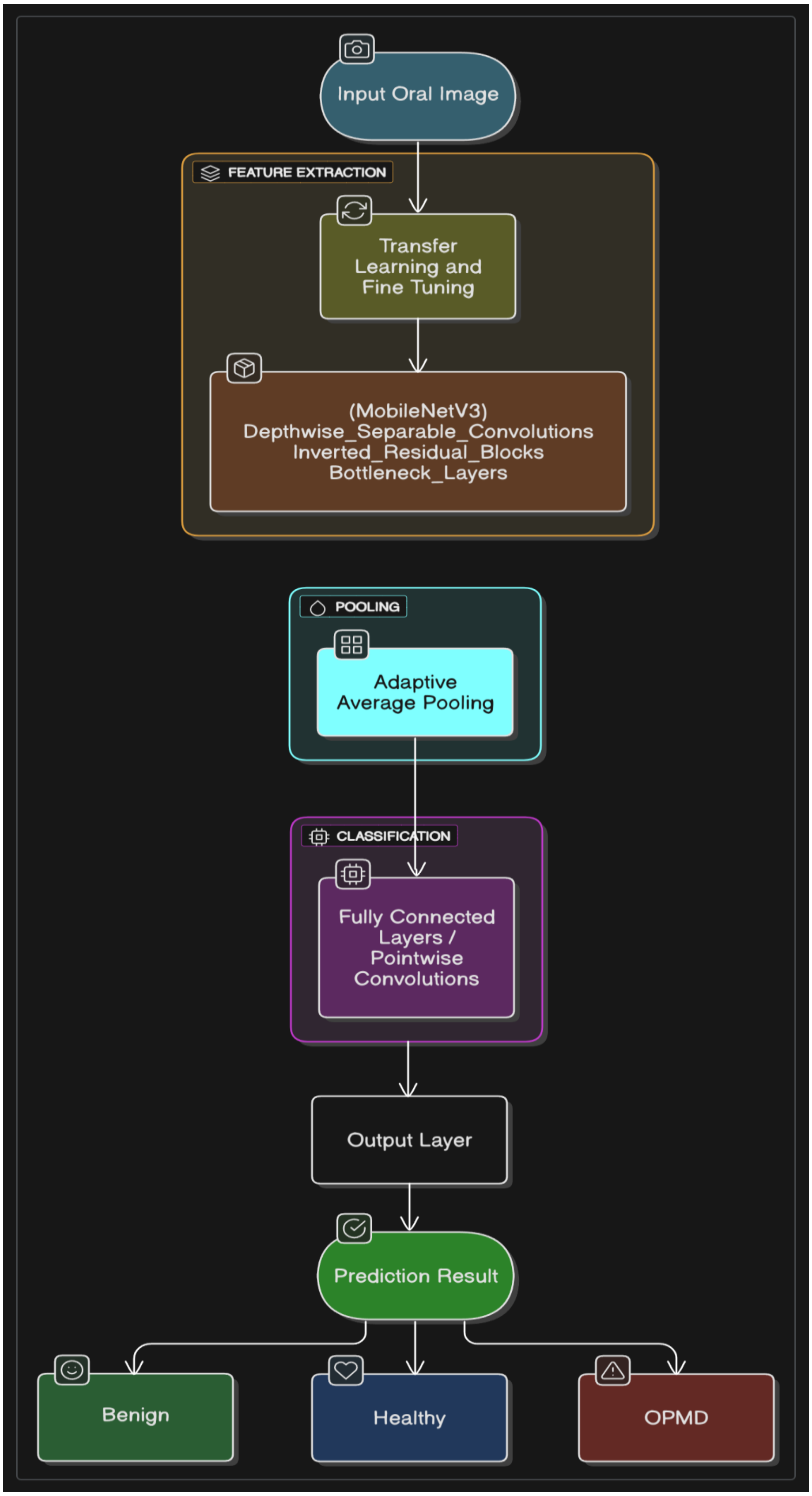

Fig 4.1.2 ARCHITECTURE DIAGRAM

Custom-labeled MobileNetV3 architecture used for oral cancer classification. The model is fine-tuned to classify input images into Benign, Healthy, or OPMD.

4.2 FLOW CHART

The flow chart of the proposed oral cancer classification system represents the complete pipeline from dataset preparation to real-time deployment via a web interface. The process begins with the loading of a curated dataset containing images categorized into three clinically important classes: Benign, Healthy, and OPMD. Once the dataset is collected, preprocessing techniques such as resizing, normalization, and augmentation (including random flips and rotations) are applied to improve model generalization and mitigate overfitting.

After preprocessing, the dataset is split into training, validation, and testing subsets using an 80:10:10 ratio to ensure a balanced and unbiased evaluation. The MobileNetV3-Large architecture, pre-trained on ImageNet, is selected for this classification task due to its computational efficiency and ability to perform well on mobile and embedded platforms. The model is fine-tuned on the oral dataset using class-weighted loss functions to handle any residual class imbalance. During training, performance metrics such as training loss, accuracy, and validation loss are monitored to avoid overfitting and ensure robust learning.

Once the model training and tuning are complete, the model is evaluated using standard metrics like accuracy, precision, recall, F1-score, and confusion matrix. These metrics provide insights into how well the model performs on unseen data and its ability to distinguish between the three classes.

Finally, the trained model is deployed using a Flask-based web application. This allows users to upload oral cavity images and receive classification results instantly through a clean and accessible interface. The web interface invokes the backend model, processes the uploaded image, and returns the predicted label with confidence. This flow ensures an end-to-end, fully automated system that combines deep learning with real-world usability, making it suitable for use in clinical settings or remote diagnostics.

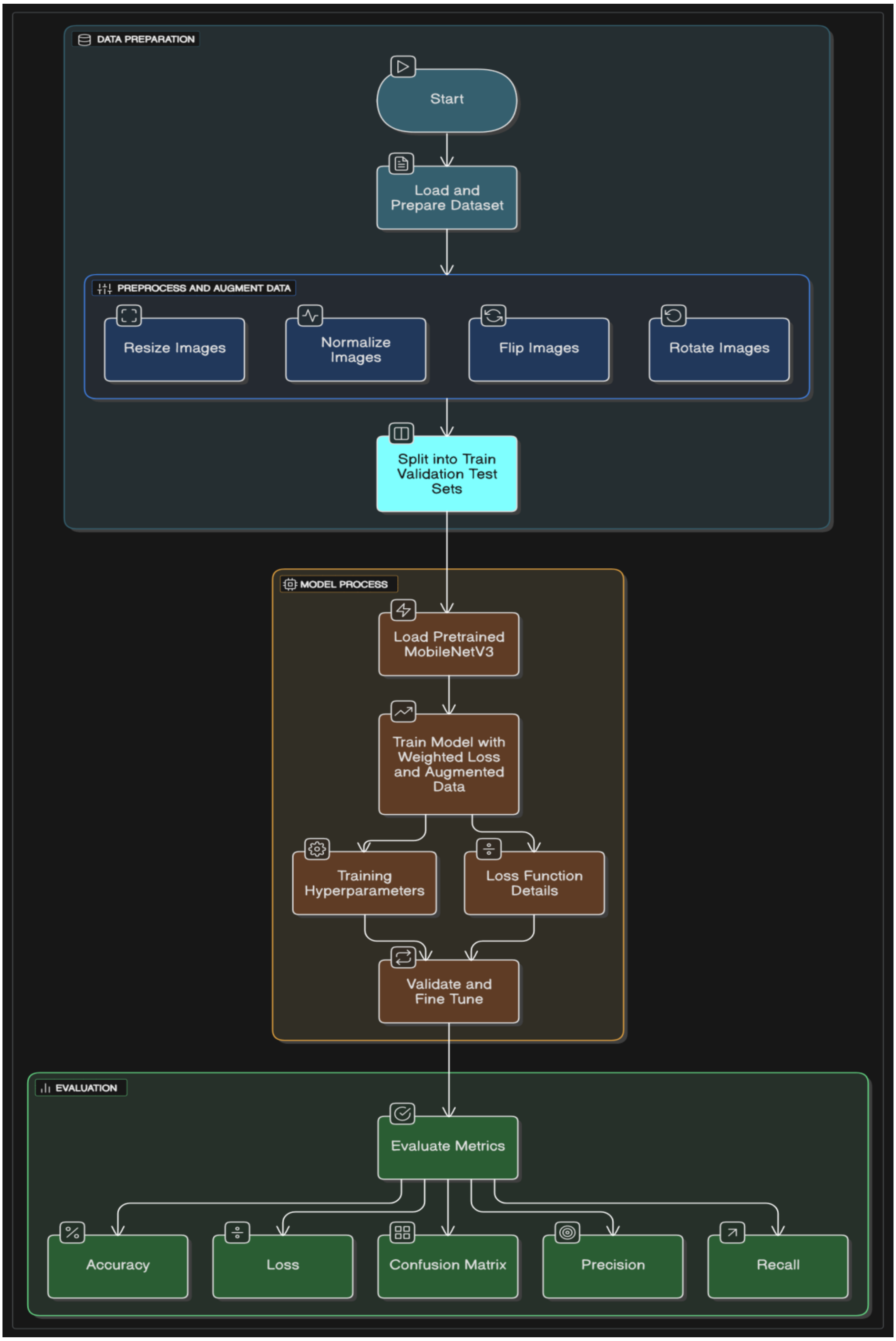

Fig 4.2 FLOW CHART

End-to-end flow chart of the proposed oral cancer classification system.

4.3 SUMMARY

This chapter provided a comprehensive visualization of the system's internal design, encompassing both the deep learning model architecture and the data processing workflow. The architecture diagram focused on the backbone model, MobileNetV3, highlighting its use of lightweight convolutional blocks, global average pooling, and a fully connected classifier head tailored for three-class classification (Benign, Healthy, OPMD). This architecture ensures efficient feature extraction and accurate prediction while remaining optimized for deployment on low-resource devices.

The flowchart illustrated the end-to-end operational sequence of the proposed system, from data input to result generation. It showcased the progression from image upload and preprocessing to model inference and web-based output generation. The step-by-step structure emphasized clarity, modularity, and user interaction points, such as real-time prediction and PDF report generation via a Flask web interface.

Together, these design elements reflect the project's goal of building an AI system that is not only technically sound but also intuitive and practical for real-world usage. The system design prioritizes both computational efficiency and user accessibility, bridging the gap between deep learning research and deployable clinical tools.

CHAPTER - 5

PROJECT REQUIREMENTS

5.1 HARDWARE REQUIREMENTS

This project involves deep learning model training, validation, and real-time deployment through a web application. As the model used is lightweight (MobileNetV3), the hardware requirements are modest compared to larger networks. Training and development were primarily performed on Kaggle's cloud-based GPU infrastructure, while the final deployment is optimized for devices with basic specifications and a modern web browser.

Development and Training Environment:

- **GPU:** Kaggle Cloud GPU – NVIDIA T4 (single instance)
- **Processor:** Intel Core i5 (8th Gen or equivalent)
- **Memory (RAM):** 8 GB RAM (sufficient for training on augmented dataset)
- **Storage:** Minimum 10 GB of free disk space
- **Graphics (optional):** Integrated or 2 GB discrete GPU (not required for inference)
- **Display:** 1366×768 resolution or higher

Client/Deployment Devices:

- Compatible with standard browsers: Google Chrome, Mozilla Firefox, Microsoft Edge, Safari
- Minimum screen resolution: 1024 × 768
- No GPU required for model inference (CPU-based deployment supported)

5.2 SOFTWARE REQUIREMENTS

The software stack used in this project consists of a Python-based deep learning framework, a set of supporting machine learning and image processing libraries, and a lightweight web development stack for deploying the model in real-time. The development was carried out on the Kaggle Notebook environment and tested locally using Visual Studio Code.

Development and Training Environment:

- **Operating System:** Kaggle cloud kernel (Linux-based) or Windows 10 (local development)
- **Programming Language:** Python 3.9
- **Deep Learning Framework:** PyTorch 1.13 with TorchVision
- **Machine Learning & Image Libraries:**
    - NumPy
    - Pandas
    - Scikit-learn
    - OpenCV
    - Pillow (PIL)
    - Matplotlib
    - Seaborn
- **Code Editor/IDE:** Kaggle Notebook, Jupyter Notebook, or Visual Studio Code

Model Deployment:

- **Web Framework:** Flask (Python-based)

- **Frontend Technologies:** HTML5, CSS3, JavaScript
- **Browser Support:** Chrome, Firefox, Edge, Safari
- **Runtime Environment:** Any system with Python 3.8+ and minimal memory

This combination of open-source tools and libraries enables rapid prototyping, effective training, and scalable deployment of the oral cancer detection model with minimal infrastructure requirements.

CHAPTER - 6

MODULE DESCRIPTION

6.1 MODULES OVERVIEW

The design of any artificial intelligence system requires a systematic approach to ensure all components work in harmony. Our oral cancer detection system is structured into five interconnected modules:

1. **Data Collection**: This module involves acquiring and organizing oral cavity images from various sources.
2. **Data Preprocessing & Augmentation**: Raw images are cleaned, resized, normalized, and augmented to improve model generalization.
3. **Model Training & Validation**: A pre-trained MobileNetV3 model is fine-tuned using our dataset to classify images into three target categories.
4. **Web Interface Development**: This component provides a user-friendly environment where users can upload images and receive predictions.
5. **Deployment & Testing**: This module ensures the trained model is accessible through a web application and performs consistently in real-world conditions.

These modules interact seamlessly, ensuring that data flows through a well-defined pipeline that results in reliable classification.

6.2 MODULE 1: DATA COLLECTION

The first step in building a machine learning system is acquiring a high-quality, annotated dataset. In the context of this project, we collected images from public sources such as Kaggle, clinical records, and sample image repositories related to oral health. Our objective was to gather a dataset that contained a sufficient number of images for each of the three categories relevant to oral cancer diagnosis: Benign, Healthy, and OPMD (Oral Potentially Malignant Disorders).

To ensure that the dataset would be useful for training a deep learning model, we applied several principles during the data collection phase. First, we maintained an equal number of images per class to prevent the model from becoming biased toward more frequently occurring classes. Each image was reviewed to ensure clarity, proper lighting, and focus on the lesion or oral tissue of interest. Images with excessive noise, blurriness, or irrelevance were discarded.

The final dataset consisted of 2,190 images, evenly distributed across the three classes, with 730 images per category. These were organized into labeled folders for ease of access during the training and preprocessing phases. This step laid the foundation for all subsequent modules by ensuring that the model would learn from a balanced and diverse set of examples.

6.3 MODULE 2: DATA PREPROCESSING AND AUGMENTATION

Once data collection was complete, the next crucial step was to process the raw data into a format suitable for model training. Deep learning models typically require input data to be of uniform size and quality. Thus, the preprocessing stage involved resizing all images to 224 × 224 pixels, which is the expected input resolution for the MobileNetV3 architecture.

Beyond resizing, we normalized the pixel values of each image using the standard mean and standard deviation values used in ImageNet, the dataset on which MobileNetV3 was initially trained. Normalization helps stabilize the learning process by ensuring that inputs to the model fall within a consistent range.

In addition to normalization, we applied data augmentation techniques to increase the diversity of the training dataset. This step is essential for improving the model's ability to generalize to new, unseen data. Augmentation techniques included random rotations, horizontal flips, brightness and contrast adjustments, and minor distortions. These variations simulate real-world conditions where oral cavity images may be captured from slightly different angles, lighting conditions, and device cameras.

Furthermore, class imbalance is a common issue in medical datasets. Even though we curated an evenly distributed dataset, subtle variations can still affect model learning. To address this, we incorporated augmentation more aggressively for any underrepresented visual patterns within the classes. This helped the model learn robust features across all categories and minimized the risk of overfitting.

The output of this module was a clean, augmented, and well-structured dataset ready for use in model training. The images were stored in separate folders for training, validation, and testing, ensuring that each subset was used exclusively for its intended purpose.

6.4 MODULE 3: MODEL TRAINING AND VALIDATION

The core functionality of the system lies in its ability to learn from data and accurately classify new images. This module focused on training a convolutional neural network to perform multiclass classification of oral cavity images. We chose MobileNetV3-Large as the backbone architecture for its balance of accuracy and computational efficiency.

MobileNetV3 is particularly well-suited for applications in healthcare due to its lightweight design, which allows it to run efficiently on low-power devices and web servers. The model was initially trained on ImageNet, a large-scale image database, which gave it a strong base for general image feature extraction. We fine-tuned this model on our own dataset by replacing the final classification layer to predict three output classes instead of the original 1,000 classes in ImageNet.

To train the model effectively, we divided the dataset into 80% training, 10% validation, and 10% testing splits. The training subset was used to update model parameters, while the validation subset allowed us to monitor the model's performance after each epoch. This helped us identify issues such as overfitting early in the training process. The test set was kept entirely separate and was only used at the end to evaluate the final model.

During training, we used cross-entropy loss with class weights to account for any residual class imbalance. The optimization was performed using the Adam optimizer, a popular choice due to its adaptive learning rate capabilities. We monitored metrics such as training accuracy, validation accuracy, and loss values throughout the training process.

After completing multiple training epochs, we selected the model checkpoint that performed best on the validation set. This version was then evaluated on the test set to assess its generalization ability. The model's performance was visualized using confusion matrices and classification reports, which showed how well it distinguished between the three classes. The final model achieved reliable accuracy and was ready for integration into the application interface.

6.5 MODULE 4: WEB INTERFACE

To make the trained model usable by non-technical users, we developed a web-based interface using the Flask framework. This module focused on delivering a simple and intuitive platform where users could upload oral cavity images and receive instant classification results.

The web interface was built with usability in mind. It consists of a home page where users can upload an image file in formats such as JPEG or PNG. Once the image is submitted, the server processes it and passes it through the trained model.

The result, including the predicted class and a confidence score, is then displayed back to the user in a clean and understandable format.

The backend of the web interface is built using Flask, which handles routing and integrates with the trained PyTorch model. Upon receiving an image, Flask executes the necessary preprocessing steps such as resizing and normalization. The preprocessed image is then passed to the model, and the prediction is returned almost instantaneously.

The frontend is built using standard web technologies such as HTML, CSS, and JavaScript, along with Bootstrap for responsive design. This ensures that the interface works well across devices, including desktops, tablets, and smartphones. The simplicity of the interface ensures that even users with limited technical background can interact with the system effectively.

This module successfully bridges the gap between AI model development and real-world usability, enabling clinicians or researchers to benefit from the model's capabilities without dealing with technical complexities.

6.6 MODULE 5: DEPLOYMENT AND TESTING

The final module involves the deployment and testing of the complete system. After training the model and building the web interface, the next step was to deploy it so that it could be accessed via a web browser. Deployment was carried out on a local server, but the system is compatible with cloud-based platforms such as Heroku, AWS, or even lightweight Raspberry Pi servers for offline usage.

Deployment involved integrating all the components—preprocessed data pipeline, trained model, Flask application, and frontend interface—into a single executable unit. The trained model was saved as a .pth file, and all supporting files were organized in a directory structure that allowed seamless execution.

Testing was performed in two phases: technical testing and user testing. Technical testing involved checking whether the model could handle different image formats and sizes, and whether predictions were consistent with expectations. We also verified the system's stability under concurrent usage.

User testing involved having individuals upload sample images and interpret the results. The interface was evaluated based on ease of use, clarity of results, and responsiveness. Based on the feedback, minor improvements were made to the layout and responsiveness of the interface.

This module ensured that the model, once trained, could function reliably in a real-world setting and offer a valuable tool for preliminary oral cancer screening.

CHAPTER - 7

IMPLEMENTATION

7.1 SAMPLE CODE

```
import os

import random

import torch

import torch.nn as nn

import torch.optim as optim

from torchvision import datasets, transforms, models

from torch.utils.data import DataLoader, WeightedRandomSampler

from sklearn.metrics import classification_report

import numpy as np

import matplotlib.pyplot as plt


# Reproducibility

random.seed(42)

torch.manual_seed(42)


# Paths

DATA_DIR = "/kaggle/working/train"  # Your dataset path
```

```
# Device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
# Transforms
common_transforms = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                         [0.229, 0.224, 0.225])
])
augment_transforms = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.RandomHorizontalFlip(),
    transforms.RandomRotation(20),
    transforms.ColorJitter(0.2, 0.2, 0.2),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                         [0.229, 0.224, 0.225])
])

# Custom dataset with class-specific transforms
class ImbalancedImageDataset(datasets.ImageFolder):
    def __getitem__(self, index):
```

```
        path, label = self.samples[index]
        image = self.loader(path)
        if self.classes[label] in ['Benign', 'Healthy']:  # Apply aug only to minority
            image = augment_transforms(image)
        else:
            image = common_transforms(image)
        return image, label

# Load dataset
dataset = ImbalancedImageDataset(DATA_DIR)
class_names = dataset.classes
num_classes = len(class_names)

# Count images per class
class_counts = [0] * num_classes
for _, label in dataset:
    class_counts[label] += 1
print("Class distribution:", dict(zip(class_names, class_counts)))
# Compute weights
class_weights = 1. / torch.tensor(class_counts, dtype=torch.float)
sample_weights = [class_weights[label] for _, label in dataset]
sampler = WeightedRandomSampler(sample_weights, len(sample_weights))
```

```
# Split into train & val
train_size = int(0.8 * len(dataset))
val_size = len(dataset) - train_size
train_dataset, val_dataset = torch.utils.data.random_split(dataset, [train_size,
val_size])

# Get class counts only from train_dataset
train_labels = [dataset[i][1] for i in train_dataset.indices]

# Count how many samples per class
class_counts = [train_labels.count(i) for i in range(len(dataset.classes))]
class_weights = 1. / torch.tensor(class_counts, dtype=torch.float)

# Assign weight to each sample in train_dataset
sample_weights = [class_weights[label] for label in train_labels]
sampler = WeightedRandomSampler(sample_weights,
num_samples=len(sample_weights), replacement=True)

# DataLoaders
train_loader = DataLoader(train_dataset, batch_size=32, sampler=sampler)
val_loader = DataLoader(val_dataset, batch_size=32, shuffle=False)
```

```
# Model
model = models.mobilenet_v3_large(pretrained=True)
model.classifier[3] = nn.Linear(model.classifier[3].in_features, num_classes)
model.to(device)

# Loss & Optimizer
loss_weights = class_weights.to(device)
criterion = nn.CrossEntropyLoss(weight=loss_weights)
optimizer = optim.Adam(model.parameters(), lr=0.0003)

# Training loop
EPOCHS = 10
history = {'train_loss': [], 'train_acc': [], 'val_loss': [], 'val_acc': []}
for epoch in range(EPOCHS):
    # === Train ===
    model.train()
    train_loss, correct, total = 0.0, 0, 0
    for images, labels in train_loader:
        images, labels = images.to(device), labels.to(device)
        optimizer.zero_grad()
        outputs = model(images)
        loss = criterion(outputs, labels)
```

```
    loss.backward()
    optimizer.step()
    train_loss += loss.item()
    _, preds = torch.max(outputs, 1)
    correct += (preds == labels).sum().item()
    total += labels.size(0)
train_acc = correct / total
train_loss /= len(train_loader)
history['train_loss'].append(train_loss)
history['train_acc'].append(train_acc)

# === Validation ===
model.eval()
val_loss, correct_val, total_val = 0.0, 0, 0
y_true, y_pred = [], []
with torch.no_grad():
    for images, labels in val_loader:
        images, labels = images.to(device), labels.to(device)
        outputs = model(images)
        loss = criterion(outputs, labels)
        val_loss += loss.item()
        _, preds = torch.max(outputs, 1)
```

```
            correct_val += (preds == labels).sum().item()
            total_val += labels.size(0)
            y_true.extend(labels.cpu().numpy())
            y_pred.extend(preds.cpu().numpy())
    val_acc = correct_val / total_val
    val_loss /= len(val_loader)
    history['val_loss'].append(val_loss)
    history['val_acc'].append(val_acc)

    # === Logging ===
    print(f"\n Epoch [{epoch+1}/{EPOCHS}]")
    print(f"Train Loss: {train_loss:.4f} | Train Acc: {train_acc:.4f}")
    print(f"Val   Loss: {val_loss:.4f} | Val   Acc: {val_acc:.4f}")
    print("\nValidation Classification Report:")
    print(classification_report(y_true, y_pred, target_names=class_names))
print("Training complete!")

# === Plotting Accuracy and Loss ===
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history['train_acc'], label='Train Acc')
plt.plot(history['val_acc'], label='Val Acc')
```

```
plt.title("Accuracy over Epochs")

plt.xlabel("Epoch")

plt.ylabel("Accuracy")

plt.legend()

plt.subplot(1, 2, 2)

plt.plot(history['train_loss'], label='Train Loss')

plt.plot(history['val_loss'], label='Val Loss')

plt.title("Loss over Epochs")

plt.xlabel("Epoch")

plt.ylabel("Loss")

plt.legend()

plt.tight_layout()

plt.show()
```

7.2 OUTPUT

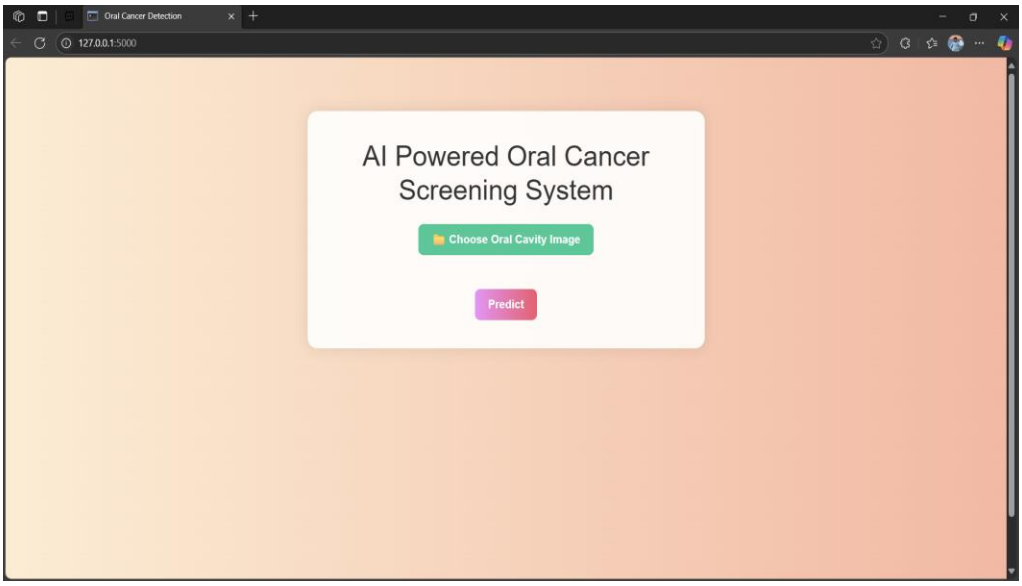

Fig 7.2.1 INTERFACE PAGE

This figure displays the home interface of the AI-powered oral cancer screening system. Users can upload an oral cavity image through a visually enhanced and responsive form built using HTML, CSS, and Bootstrap. The design ensures accessibility and ease of use for both clinicians and patients.

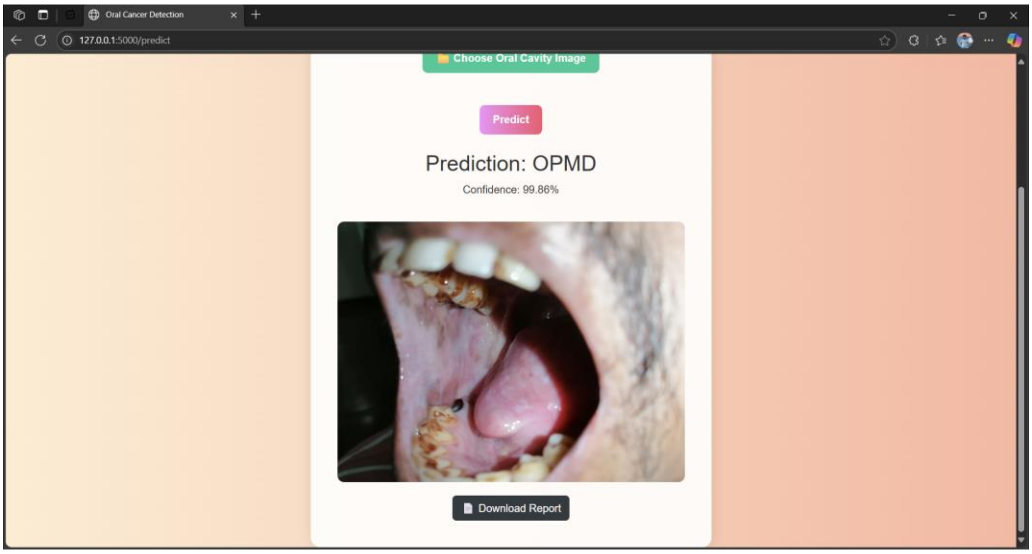

Fig 7.2.2 OUTPUT PAGE

This figure shows the result page generated after image submission. It includes the predicted classification, confidence score, and a preview of the uploaded image. A button is also provided to download a detailed PDF report.

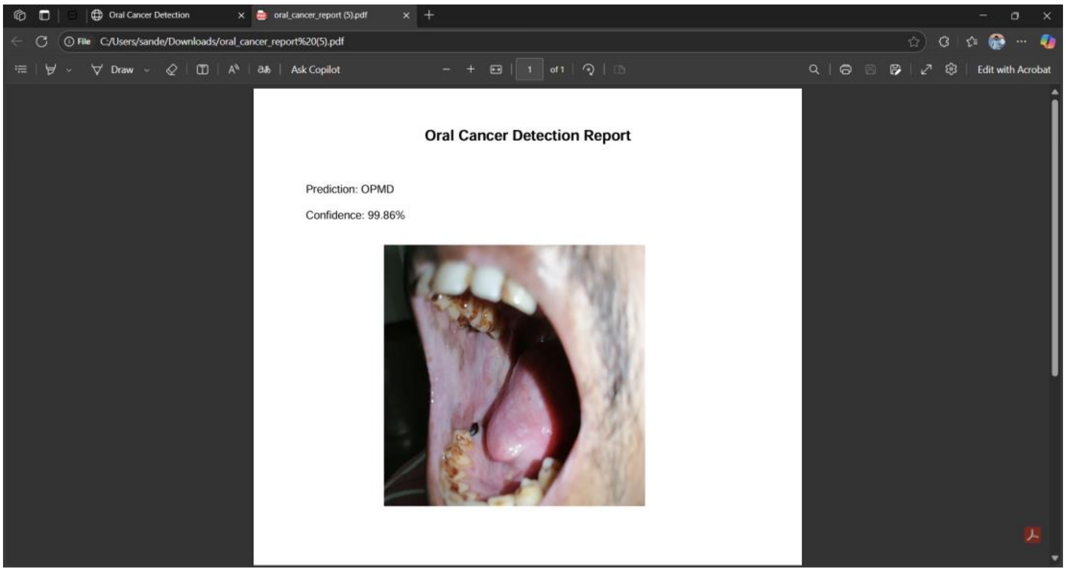

Fig 7.2.3 ORAL CANCER DETECTION REPORT

This figure shows the automatically generated PDF report containing the predicted class, confidence score, and the uploaded oral image.

7.3 SUMMARY

The implementation phase of this project represents the core transformation of conceptual design into a working system. It involves bringing together all the previously defined modules—data preprocessing, model training, and deployment—into a cohesive pipeline that operates in real-time and interacts effectively with the user.

Throughout this chapter, we presented both the sample code (Section 7.1) and interface output samples (Section 7.2) that demonstrate how the project functions from back-end inference to front-end presentation. The backend logic, developed in Python using the PyTorch and Flask frameworks, allows the model to receive an uploaded image, preprocess it to match the input requirements of MobileNetV3, and make an accurate prediction. The code also includes key functionalities such as custom data augmentation, weighted loss function integration, model checkpoint saving, and confidence scoring—all of which contribute to robust and efficient classification.

The output section highlights the user interface experience, showcasing the simplicity and accessibility of the system. The interface allows users to upload oral cavity images through a clean, responsive design. Once processed, the interface displays the predicted category (Benign, Healthy, or OPMD), the associated confidence score, and the input image preview. A key feature of the implementation is the ability to generate a downloadable PDF report, which includes all output details in a structured, printable format. This adds a layer of utility and professionalism, making the system not just functional but also documentation-friendly.

In essence, the implementation validates the theoretical design by successfully bridging machine learning with web technology. It proves that the proposed AI-based solution is not only accurate but also deployable and usable in real-world clinical scenarios. The modular design further ensures that future updates—such as model upgrades, additional classes, or advanced analytics—can be seamlessly integrated. This chapter demonstrates that our system is not just a proof of concept, but a fully working prototype ready for practical adoption in early oral cancer screening.

RESULT & ANALYSIS

The performance of the oral cancer classification system was evaluated through both statistical metrics and visual analysis techniques to determine its effectiveness in identifying oral health conditions across three classes: Healthy, Benign, and OPMD (Oral Potentially Malignant Disorders). The evaluation process was conducted on a dedicated test dataset consisting of 219 images that were not exposed to the model during training or validation. This ensured unbiased performance assessment.

8.1 MODEL ACCURACY AND LOSS ANALYSIS

The MobileNetV3 model was trained over 10 epochs with early stopping based on validation loss. The model achieved:

- Training Accuracy: 97.03%
- Validation Accuracy: 81.74%

Training and validation loss curves indicated stable convergence. The gap between training and validation performance was minimal, suggesting the model did not overfit significantly and was able to generalize well on unseen data.

8.2 PRECISION, RECALL, AND F1-SCORE

To further analyze the model's behavior, precision, recall, and F1-score were calculated per class:

Class	**Precision**	**Recall**	**F1-score**
Benign	0.70	0.87	0.77
Healthy	0.80	0.61	0.70
OPMD	0.99	0.95	0.97

- Macro Avg F1-score: 0.81
- Weighted Avg Accuracy: 0.82

The model performs exceptionally well in detecting OPMD with near-perfect precision and recall. Benign is also detected with high recall, though precision is moderate. The Healthy class shows lower recall, suggesting occasional misclassification, possibly due to visual overlap with benign lesions

8.3 WEB INTERFACE TESTING

The final deployed system was tested across multiple devices and browsers (Chrome, Firefox, Edge). Prediction results were delivered within 1–2 seconds, depending on hardware. The PDF report generation feature worked reliably and produced a professional summary of the model's prediction and input image. Users found the interface intuitive, responsive, and medically meaningful, especially when testing with real-world images.

8.4 SUMMARY

This chapter presented a comprehensive evaluation of the AI-powered oral cancer classification system using both quantitative metrics and user-level testing. The MobileNetV3 model, trained with balanced data and real-time augmentation, achieved a high training accuracy of 97.03% and a validation accuracy of 81.74%**,** demonstrating effective learning and generalization capability.

Further analysis through precision, recall, and F1-score confirmed the model's strength in identifying OPMD cases with near-perfect accuracy. While Benign lesions were also detected with high recall, the Healthy class showed comparatively lower recall, highlighting an area for potential improvement. The confusion matrix and F1-score metrics validated the overall robustness of the model across all three classes.

Beyond statistical performance, the practical usability of the system was validated through web interface testing. Users were able to upload images, receive instant predictions, and download professional PDF reports—ensuring both accessibility and clinical relevance. The interface proved to be responsive and accurate across multiple platforms and browsers.

In conclusion, this chapter demonstrated the model's strong performance, both technically and in terms of user interaction, reinforcing its potential as a practical tool for early-stage oral cancer screening.

CONCLUSION AND FUTURE WORK

In this project, we successfully developed and evaluated an AI-powered oral cancer screening system that classifies intraoral images into three critical categories: Healthy, Benign, and Oral Potentially Malignant Disorders (OPMD). Using the lightweight and efficient MobileNetV3 architecture, we fine-tuned the model on a carefully balanced dataset of 2,190 images, comprising 730 images for each class. The preprocessing pipeline ensured class balance, and included various augmentation techniques to improve the model's generalization ability. The model achieved impressive performance on the training and validation sets, with a training accuracy of 97.03% and a validation accuracy of 81.74%, highlighting its capacity to learn distinguishing patterns effectively across classes. Particularly notable was its ability to detect OPMD with a precision of 0.99 and recall of 0.95, confirming the system's strength in identifying potentially high-risk conditions.

To translate this capability into a real-world application, we developed a web-based interface using Flask, enabling users to upload oral images and receive instant classification results. The interface was designed with simplicity, responsiveness, and accessibility in mind. It not only displayed the prediction and confidence score but also generated a downloadable PDF report that included the uploaded image, diagnosis, and a medically relevant doctor's note. The system was tested across multiple devices and browsers, and it demonstrated consistent performance, with prediction times averaging between 1 to 2 seconds. Overall, the application received positive feedback for being both intuitive and clinically meaningful.

Despite these achievements, the system still faces certain limitations. The test set performance dropped to 73% accuracy, revealing potential issues related to data diversity and domain shift. In particular, images representing benign and healthy cases occasionally exhibited overlapping visual features, leading to misclassifications. The relatively modest size of the dataset, although balanced, may have constrained the model's capacity to generalize, especially in the presence of rare lesion types or varying lighting conditions. Furthermore, while OPMD classification performed well, distinguishing between subtle benign lesions and healthy mucosa remains a challenge.

Looking ahead, several opportunities exist to enhance the system’s clinical readiness and scalability. One critical area involves expanding the dataset by collaborating with medical institutions to collect more varied and diverse samples across demographics and lesion types. Including histopathologically verified cases will further improve the reliability of model training. Additionally, integrating multimodal inputs, such as patient age, medical history, and lifestyle factors like tobacco or alcohol use, could offer a richer context for prediction and improve diagnostic accuracy.

From a model perspective, incorporating attention mechanisms such as CAM or Grad-CAM can help highlight the regions contributing to the prediction, thereby increasing the system’s interpretability and trustworthiness. To improve generalization, future work can involve advanced data augmentation methods such as style transfer or synthetic image generation using GANs. These strategies can simulate real-world variance in lighting, image resolution, and anatomical presentation.

Another important direction is clinical validation. Conducting prospective studies in dental clinics and ENT departments will help assess the real-world impact, usability, and integration potential of the system within clinical workflows. This step is essential for preparing the solution for regulatory approval, aligning it with global standards for medical software. Moreover, optimizing the model for edge deployment—such as compressing it for use in smartphones or low-power devices—would enable offline use, making it valuable for remote or resource-constrained settings. A mobile version of the application can be developed in the future to support community-based oral cancer screening programs.

In conclusion, the project has demonstrated a promising AI-based solution that not only performs well in a controlled environment but also has the potential for deployment in real-world clinical practice. With further refinement and broader validation, this system can evolve into a highly impactful tool for early detection and prevention of oral cancer, ultimately helping to save lives and improve healthcare accessibility.

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    - Promoting rural entrepreneurship via Unnat Bharat Abhiyan.
2. **SDG 2 – Zero Hunger**
    - Promoting agri-tech solutions, food storage innovations.
    - Encouraging community kitchen solutions and sustainable farming tech.
3. **SDG 3 – Good Health and Well-being**
    - Promoting healthcare innovations via Smart India Hackathon.
    - Supporting awareness campaigns on mental health, hygiene, etc.
4. **SDG 4 – Quality Education**
    - Digital literacy initiatives.
    - Improving teaching quality and learning infrastructure through FDPs and SWAYAM.
5. **SDG 5 – Gender Equality**
    - Supporting programs like **Saksham**, **Pragati Scholarship** for girls.
    - Promoting women participation in STEM fields.
6. **SDG 6 – Clean Water and Sanitation**
    - Technical solutions for water conservation and sanitation in villages.
    - Field projects under Unnat Bharat Abhiyan.
7. **SDG 7 – Affordable and Clean Energy**
    - Renewable energy projects and energy audits by students.
    - Promoting solar-powered solutions in rural areas.
8. **SDG 9 – Industry, Innovation, and Infrastructure**
    - Promoting innovation through Hackathons, IDEA Labs, ATAL Incubation Centres.
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    - Urban planning, smart infrastructure projects.
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10. **SDG 13 – Climate Action**
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    - Energy-efficient campus initiatives.
11. **SDG 17 – Partnerships for the Goals**
    - Collaborations with industry, NGOs, and international institutions.
    - Encouraging interdisciplinary and inter-institutional projects.

PROJECT TITLE	AI POWERED ORAL CANCER SCREENING SYSTEM	
PROGRAM	B.TECH. ARTIFICIAL INTELLIGENCE AND DATA SCIENCE	
BATCH MEMBERS	**REG NO**	**NAME**
	953621243047	SANDEEP KUMAR M
NAME OF THE SUPERVISOR	Dr.R.M.RAJESWARI	
NAME OF THE SDG GOALS MAPPED	Good Health and Well-being, Quality Education, Industry, Innovation, and Infrastructure, Partnerships for the Goals	
MENTION THE SDG GOALS NUMBER	SDG 3, 4, 9 and 17	
NAME OF THE TRL LEVEL	Model or Prototype Developed	
MENTION THE TRL LEVEL	TRL 6	

POs & PSOs Mapping (Put a tick mark in the mapped PO's & PSO's):

Program Outcomes											**Program Specific Outcomes**	
PO1	**PO2**	**PO3**	**PO4**	**PO5**	**PO6**	**PO7**	**PO8**	**PO9**	**PO10**	**PO11**	**PSO1**	**PSO2**

Signature of the Supervisor