

THERMAL IMAGING OF ORAL DISEASES

Submitted in partial fulfillment of the requirements for the award of Bachelor
of Science in Biotechnology

PROJECT REPORT

By

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SATHYABAMA

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

CATEGORY-1 UNIVERSITY BY UGC

Accredited with Grade "A++" by NAAC | 12B Status by UGC

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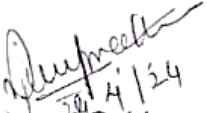
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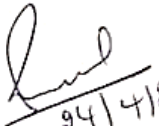
BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **T. Khushi** (Reg No. **41770014**) who carried out the project entitled "**Thermal Imaging of Oral Diseases**" project under my supervision from October 2023 to April 2024.


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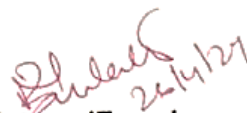
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ABSTRACT

Thermal imaging, a non-invasive imaging technique, has emerged as a promising tool for the early detection and monitoring of various diseases, including those affecting the oral cavity. This study aims to evaluate the utility of thermal imaging in identifying and monitoring oral diseases, such as periodontal diseases, dental caries, and oral cancer. The application of thermal imaging in oral health assessment, diagnosis, and monitoring were identified and analyzed. Thermal imaging offers several advantages for the assessment of oral diseases, including its non-invasiveness, rapidity, and ability to provide real-time, quantitative data. Studies have demonstrated that changes in temperature patterns of oral tissues can be indicative of underlying pathologies, such as inflammation, infection, or neoplastic growth. Furthermore, thermal imaging can complement conventional diagnostic methods by providing additional information on the extent and severity of oral diseases. Thermal imaging is a valuable adjunctive tool for the early detection and monitoring of oral diseases. Further research is to standardize imaging protocols, establish diagnostic criteria, and validate the clinical utility of thermal imaging in routine dental practice. Integration of thermal imaging into oral health screening programs has the potential to improve early detection, facilitate timely intervention, and enhance patient outcomes in the management of oral diseases.

Keywords: Thermal imaging, oral diseases, periodontal diseases, dental caries, oral cancer, diagnosis, monitoring, non-invasive imaging, early detection, oral health assessment.

TABLE OF CONTENTS

CHAPTER NO	TITLE	PAGE NO
	CONTENT	VI
	LIST OF FIGURES	VIII
1	INTRODUCTION	1
2	LITERATURE SURVEY	7
3	AIM AND SCOPE	10
4	MATERIALS AND METHODS	11
	4.1 Place of work	11
	4.2 Thermal camera	11
	4.2.1 About Camera	12
	4.2.2 Thermal Image	16
	over Digital X-ray	
	4.2.3 Advantages of	17
	Thermal Camera	
	4.2.4 Disadvantages of	19
	thermal camera	
	4.3 Methodology	20
	4.3.1 Deep Learning	29
	Model	
	4.3.2 Resnet-18	30
	4.3.3 Resnet-50	32
	4.3.4 Darknet-53	34
	4.3.5 Darknet-19	36
	4.3.6 VGG-16	38
	4.3.7 Squeezenet	39

5	RESULTS	AND	42
	DISCUSSION		
6	SUMMARY	AND	47
	CONCLUSION		
	REFERENCE		48

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE NO.
4.1	Patients undergoing dental treatment at Sathyabama Dental Hospital	11
4.2	Feature of thermal camera from the front view	14
4.3	Feature of thermal camera from the rear view	14
4.4	Parameter of thermal camera	15
4.5	Real time application of thermal camera	15
4.6	Normal, thermal & X-ray images of patient 1	23
4.7	Normal, thermal & X-ray images of patient 2	24
4.8	Normal, thermal & X-ray images of patient 3	25
4.9	Normal, thermal & X-ray images of patient 4	26
4.10	Normal, thermal & X-ray images of patient 5	27
5.1	Graph of Resnet-50 training	42
5.2	Graph of Resnet-18 training	43
5.3	Graph of Darknet-19 training	44
5.4	Graph of Squeeze net training	45
5.5	Graph of VGG-16 training	46

CHAPTER - 1

INTRODUCTION

Thermal imaging, also known as infrared thermography, presents a promising alternative for oral disease detection by capturing thermal patterns emitted from the body's surface. Thermal imaging is an effective Radiation-free way to examine oral health issues and pain conditions. A healthy jaw will have even heat patterns throughout while inflammation will appear at the highest temperature on a thermal image. It emerged as a promising diagnostic tool in dentistry for the detection and monitoring of oral diseases. The detection of infrared radiation emitted by objects based on their temperature and a basic idea behind thermal imaging. In modern healthcare, the integration of advanced technologies has revolutionized diagnostic procedures, enabling more efficient and accurate detection of various medical conditions. One such innovative technique gaining traction in dentistry is thermal imaging, which offers a non-invasive and radiation-free approach to detecting oral disease.

Thermography is a process where a (thermal) camera captures and generates an image by using infrared radiation, emitted from an object. The image provides an opportunity to visibly record invisible (to the human eye) infrared energy or heat. Thermography is a non-invasive, non-contact, user-friendly, and portable imaging method and has been used in various industrial fields, such as engineering and construction.

Thermography is now an evolving and expanding field in medicine as a diagnostic tool, currently used to diagnose vascular malformations, and thyroid nodules, and differentiate different intraocular tumors. Specific to medicine, thermography is a field of science that analyzes and records the biothermal changes in various structures to assess health or disease. Using infrared radiation, a pixel map, also known as a thermogram, is generated to record biothermal change. Each temperature change is defined with a different color. A thermogram with fewer colors due to less heat production may suggest areas of poor blood circulation, and vice versa.

Thermography has had limited use in dentistry, but with recent technological advances, thermography has been employed for the production of digital

images to assess changes in the temperature of restorations, and inflamed periodontal tissue disease of the temporomandibular joints and detect intraosseous temperature changes during dental implant placement. Thermography has recently been used to monitor inflammation after dental surgeries and has shown promise as a tool to diagnose pathological conditions. Digital dentistry technologies tend to have limited use, due to the high cost of equipment, and software, and the challenging workflow. Dental thermography has also faced these challenges. This report explores the development of a novel dental thermal imaging application that is simple, cost-effective, and efficient. Oral diseases encompass a wide spectrum of conditions affecting the oral cavity, including dental caries, periodontal diseases, and oral cancers. Early detection and intervention are critical for effective management and prevention of complications associated with these conditions. Traditional diagnostic methods often rely on visual inspection, palpation, and radiographic imaging, which may have limitations in detecting early-stage or subtle changes.

This technique relies on the principle that diseased or inflamed tissues exhibit altered thermal characteristics compared to healthy tissues. By detecting these temperature variations, thermal imaging can provide valuable insights into the presence and extent of oral pathologies. Unlike conventional diagnostic modalities, thermal imaging is non-contact and non-invasive, making it well-suited for use in sensitive areas such as the oral cavity. Moreover, it does not involve exposure to ionizing radiation, eliminating concerns associated with traditional radiographic techniques. This makes it particularly appealing for patients like pregnant women, and individuals with radiation sensitivity.

The application of thermal imaging in dentistry extends beyond disease detection to include monitoring treatment outcomes and assessing oral health status over time. By capturing thermal data longitudinally, clinicians can track changes in temperature patterns indicative of disease progression or treatment response.

This proactive approach enables early intervention and personalized treatment strategies tailored to individual patients' needs. Human thermography for various disease diagnoses will mainly focus on detection using thermography-based health monitoring systems and diagnostic tools.

- A. Infrared Thermography for Cancer Detection
- B. Infrared Thermography for Diabetes Diagnosis
- C. Thermography for Diagnosis of Liver Diseases
- D. Thermography for Oral Diseases
- E. Infrared Imaging for Detecting Novel COVID-19 Virus

Currently, infrared thermography shows a continued growth in modern medicine, explained by the technological advantages of the method in the prevention, the monitoring of some diseases, the selection and evaluation of treatments, and its high diagnostic sensitivity and specificity reported by specialized studies. Recent traditional medicine focused primarily on the diagnosis and treatment of diseases, towards a modern approach to medicine aimed at preventing diseases through the identification and elimination of risk factors, thus opening new horizons regarding the applicability of thermography in several medical fields.

A series of functional disorders can be identified based on thermographic images, such as metabolic or vascular subcutaneous disorders, acute and chronic inflammatory processes, formation and development of tumor structures, degenerative changes, disturbances within some organs or structures with strong vascularization (including maxillofacial structures). For these reasons, and due to the perfecting of image processing techniques, and the increase of the sensitivity of thermal sensors and spatial resolution, the medical fields in which thermography has proven itself as a diagnostic method have become more numerous. Thus, diagnostic thermography has been recognized and successfully applied so far in specialties such as rheumatology, dermatology, oncology, orthopedics, cardiology, neurology, angiology, occupational medicine, forensic medicine, general surgery,

endocrinology, pediatrics, ophthalmology, and to an ever-increasing extent dentistry.

In the case of dental medicine, infrared thermography appeared and grew as a necessity for the correlation of oral health with general health, opening new diagnostic directions along with conventional paraclinical investigations practiced in this area. Although small in applicability compared to general medicine, studies have been conducted in dentistry, and reproducible results have been registered in endodontics, odontology, temporomandibular joint (TMJ) pathology, oral and maxillofacial (OMF) surgery, anesthesia, implantology, prosthodontics, and beyond.

Despite its potential benefits, the widespread adoption of thermal imaging in dentistry requires further validation through rigorous research and clinical trials. Challenges such as standardization of imaging protocols, interpretation of thermal patterns, and integration into existing diagnostic workflows need to be addressed to maximize its clinical utility.

Thermal cameras have numerous real-world applications across various industries and sectors. Here are some specific examples:

Building Inspections

Thermal cameras are used to identify energy inefficiencies in buildings by detecting heat loss or air leaks. They help locate moisture intrusion, which can lead to mold growth and structural damage. Inspectors use thermal imaging to identify faulty electrical connections, overloaded circuits, and overheating components.

Industrial Maintenance

In industrial settings, thermal cameras detect overheating machinery components, such as bearings, motors, and conveyor belts, indicating potential failures.

They assist in predictive maintenance programs by identifying equipment issues before they lead to costly downtime or accidents.

Firefighting and Search & Rescue:

Firefighters use thermal cameras to navigate through smoke-filled environments and locate victims in burning buildings. Thermal imaging helps identify hotspots within structures and assess the spread of fires, aiding in firefighting efforts.

Search and rescue teams utilize thermal cameras to locate missing persons, whether in wilderness areas or urban environments.

Law Enforcement and Security:

Law enforcement agencies use thermal cameras for surveillance, tracking suspects, and locating hidden individuals. Thermal imaging assists in border security by detecting illegal crossings, smugglers, and wildlife trafficking. Security personnel use thermal cameras for perimeter surveillance and intruder detection, especially in low-light conditions.

Medical Diagnostics:

Thermal cameras are used in medical diagnostics to detect abnormalities in blood flow, diagnose vascular disorders, and monitor inflammation. They assist in identifying hotspots associated with infections, tumors, or injuries. Infrared thermography is used in breast cancer screening as a non-invasive technique to detect early signs of the disease.

Environmental Monitoring

Thermal cameras help monitor wildlife populations, studying behavior patterns and habitat usage. Environmental agencies use thermal imaging to detect wildfires, assess vegetation health, and monitor industrial emissions. In agriculture, thermal cameras aid in irrigation management, pest control, and crop health monitoring by detecting variations in plant temperature.

Consumer Applications

Thermal cameras are integrated into smartphones, allowing users to capture thermal images and videos for personal use, such as home inspections, outdoor activities, and pet care. They are also used in automotive applications for night vision systems, detecting pedestrians and animals on

the road.

These real-world applications highlight the versatility and utility of thermal cameras across a wide range of industries, contributing to safety, efficiency, and decision-making processes.

In conclusion, thermal imaging holds promise as a valuable tool for the detection and management of oral diseases. Its non-invasive nature, lack of ionizing radiation, and ability to capture subtle temperature variations make it an attractive adjunctive diagnostic modality in dentistry. Continued technological advancements and research efforts are essential to harness the full potential of thermal imaging and improve oral healthcare outcomes for patients worldwide.

CHAPTER-2

LITERATURE SURVEY

Wziątek-Kuczmik, *et al.*, (2023) Thermal Imaging of Tongue Surface as a Prognostic Method in the Diagnosis of General Diseases-Preliminary Study. This work aimed to develop an original method of thermographic measurement of tongue temperature as a prognostic method in the diagnosis of general diseases.

Aboushady, *et al.*, (2021) aim was to assess the validity of thermography in diagnosing periapical inflammatory lesions, including acute pulpitis with apical periodontitis (AAP), acute periapical abscess (AA), and chronic periapical abscess (CA). The researchers enrolled 80 patients and used clinical and radiographic criteria for diagnosing these conditions. Thermographic data were acquired using the FLIR E-5 Infrared Camera, both intraorally and extraorally, and temperature ranges for each diagnostic subgroup were measured.

Biagioni, *et al.*, (1996) author provide an overview of these advanced techniques and their previous applications within dentistry. Through the presentation of a pilot study, potential future applications in the assessment of craniomandibular disorders are elucidated. Traditionally, infrared thermography faced challenges such as low sensitivity and a lack of real-time imaging capabilities. However, contemporary systems have overcome these limitations, offering enhanced sensitivity and the ability to capture and digitize thermal data in real time. This technological progress has paved the way for the broader utilization of infrared imaging in dental research and clinical practice. Previous applications of infrared thermography in dentistry have included the assessment of various conditions such as orofacial pain, temporomandibular disorders, and dental pulp vitality. These studies have demonstrated the feasibility and potential benefits of using thermography as a diagnostic tool in dentistry.

Mouli, *et al.*, (2012) author conducted a Thermography, a method for measuring skin temperature distribution over time, which has been utilized for over four decades to assess the body's heat dissipation. The underlying principle of thermography relies on the correlation between blood circulation variations indifferent skin layers and corresponding temperature changes. Consequently, conditions affecting blood flow can manifest as abnormalities in temperature distribution, offering valuable diagnostic insights.

Les Kalman (2022) predicted that thermography, a process utilizing thermal cameras to capture and generate images through infrared radiation emitted from objects, has historically seen limited utilization in dentistry. However, recent technological advancements have led to the development of digital thermography in dentistry. One notable advancement is the creation of the Dental Thermal App (DTA), an Android software application designed to offer a straightforward, cost-effective, and clinically-based workflow for thermal imaging in dental practice.

Girkin, *et al.*, (2021) conducted early detection and management of dental caries are critical for preventing the progression of lesions into cavities, thus avoiding the need for invasive "drill-and-fill" treatments. However, early-stage caries lesions often manifest as subtle white spots against a predominantly white background, making them challenging to identify before they advance to cavities. To address this limitation, a spatial frequency domain imaging technique has been proposed to characterize the optical properties of dental tissue.

Sebastien Jean Mambou , *et al.*, (2018) The novel contribution of this paper lies in conducting a comparative analysis of existing breast cancer detection methods, with a focus on infrared imaging augmented by sophisticated computer vision algorithms and deep learning models. By synthesizing findings from previous research and leveraging cutting-edge technologies, this study aims to provide insights into the efficacy and potential of infrared imaging as a tool for early breast cancer detection.

Camille L Stewart, *et al.*, (2018) This review will begin by outlining key issues associated with metastatic colorectal cancer to the liver, including available treatments and their efficacy. Surgical and ablative procedures for treating extrahepatic metastases have gained increasing acceptance and have demonstrated effectiveness in alleviating symptoms and prolonging life. Specifically, this literature survey will address the management of metastases in sites such as the lung, lymph nodes, peritoneum, bone, and brain. It will provide an overview of the best available evidence regarding treatment strategies, including surgical interventions and ablative procedures, while also exploring potential new directions in the field. By synthesizing existing research and clinical evidence, this review aims to provide insights into the current landscape of metastatic colorectal cancer management beyond liver metastases. It will highlight the evolving role of surgical and ablative therapies in addressing extrahepatic metastases and discuss emerging strategies for improving patient outcomes and quality of life.

Selvarani, *et al.*, (2019) This literature survey proposes the analysis of thermal images of the tongue as a potential diagnostic tool for identifying diabetes mellitus at an early stage. By examining thermal patterns and temperature variations in the tongue, this approach aims to provide a non-invasive and efficient method for detecting systemic changes associated with diabetes mellitus. Through synthesizing existing research and clinical evidence, this survey seeks to explore the feasibility and effectiveness of utilizing tongue thermal imaging as a diagnostic modality for early detection of diabetes mellitus, thereby facilitating timely intervention and improved management of the condition.

CHAPTER 3

AIM AND SCOPE

3.1 AIM

To study and assess the technique of thermal imaging for diseasediagnosis and prognosis of Dentistry.

3.2 SCOPE

- Thermal imaging enables the early detection of oral diseases by capturing temperature variations within the oral cavity, often before visible symptoms manifest.
- Thermal imaging allows for the monitoring of disease progression and treatment overcomes over time.
- It can help distinguish between benign and malignant lesions based on their thermal signatures.
- It facilitates the assessment of treatment response in patients undergoing therapy for oral diseases.
- Thermal imaging serves as a platform for research and innovation in dentistry

CHAPTER 4

MATERIALS AND METHODS

4.1 PLACE OF WORK



Fig 4.1 Patients undergoing dental treatment at Sathyabama Dental Hospital

4.2 THERMAL CAMERA

- FLIR (Forward Looking Infrared) thermal camera are devices that use infrared radiation to create images based on the temperature differences to object in their field of view.
- A FLIR thermal camera can detect tiny differences in heat – as small as 0.01°C to accurately measure temperatures up to 400°C with different color palettes.
- Thermal imaging camera use color to show the relative temperature of objects: Extreme hot is white, hot is red, moderate is yellow, less is green, and cold is blue
- FLIR thermal camera detects the heat emitted by objects in the form of

infrared radiation, warmer objects emit more infrared radiation than cooler ones.

- The camera's sensor converts the infrared radiation into electrical signals into a visual representation of temperature differences.

4.2.1 About Camera

Thermal imaging cameras, such as those produced by FLIR Systems, are invaluable tools used in various industries and applications. These cameras operate by detecting infrared radiation emitted by objects, converting it into a visible image, and allowing users to see temperature variations.

FLIR, which stands for Forward Looking Infrared, is a prominent manufacturer of thermal imaging cameras, offering a wide range of products tailored to different needs, from industrial inspections to security and surveillance.

One key aspect of FLIR's thermal cameras is their ability to visualize temperature differences with high accuracy. This makes them essential in fields like building diagnostics, where they can identify heat loss or insulation problems, and in electrical maintenance to detect overheating components, potentially preventing equipment failures and fires.

In the realm of security and law enforcement, thermal cameras can aid in surveillance, search and rescue operations, and border monitoring. Their ability to detect heat signatures allows for enhanced situational awareness, even in low-light conditions or dense foliage.

In recent years, FLIR has also integrated thermal imaging technology into consumer products, such as smartphone attachments and wearable devices, bringing thermal imaging capabilities to a broader audience.

Principle of Operation: Thermal imaging cameras work by detecting the heat (infrared radiation) emitted by objects. They use sensors called microbolometers to capture this radiation. The captured data is then processed to generate a visual representation of the temperature differences within the scene, creating a thermal image.

Applications:

Security: Thermal cameras are used for surveillance in low-light conditions or areas with poor visibility. They can detect people or animals based on their

body heat signatures.

Industrial Inspections: FLIR cameras are commonly used in industries like electrical, mechanical, and building inspections to identify hotspots, leaks, or faulty components.

Search and Rescue: Thermal cameras are invaluable tools for locating missing persons or survivors in various environments, including dense forests, snow, or rubble.

Medical Imaging: In the medical field, thermal cameras can be used to detect abnormalities in blood flow, monitor body temperature, and diagnose certain conditions like inflammation or vascular disorders.

Features:

Resolution: FLIR cameras come in various resolutions, ranging from low to high definition, allowing users to capture more detailed thermal images.

Portability: Some FLIR cameras are designed to be handheld, while others are mounted on drones, vehicles, or other platforms for aerial or mobile thermal imaging.

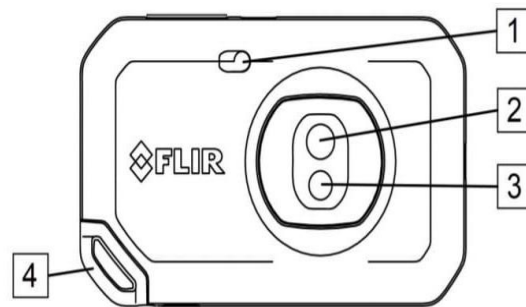
Image Enhancement: Many FLIR cameras offer features like image blending, which overlays thermal and visible light images to provide better context and interpretation.

Connectivity: Modern FLIR cameras often come with Wi-Fi or Bluetooth connectivity, allowing users to transfer images wirelessly to other devices for analysis or storage.

Cost: The cost of FLIR cameras can vary significantly depending on factors like resolution, features, and intended application. Entry-level models are available for a few hundred dollars, while high -end professional-grade cameras can cost several thousand dollars or more.

Advancements: FLIR continuously innovates its technology, introducing new features such as higher resolutions, improved image processing algorithms, and integration with other devices and platforms.

Overall, FLIR's thermal imaging cameras play a vital role in various sectors, offering valuable insights that are often inaccessible to the naked eye or traditional imaging technologies.



- 1. Camera lamp.
- 2. Infrared lens.
- 3. Visual camera lens.
- 4. Lanyard attachment point.

Fig.4.2 Feature of Thermal Camera from front view

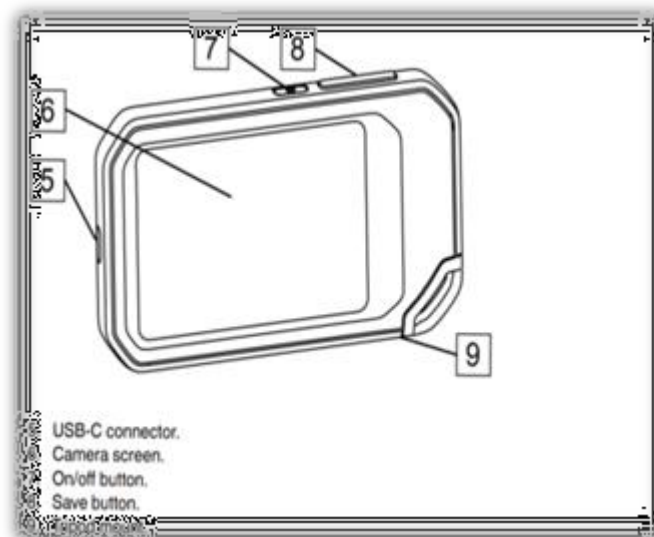
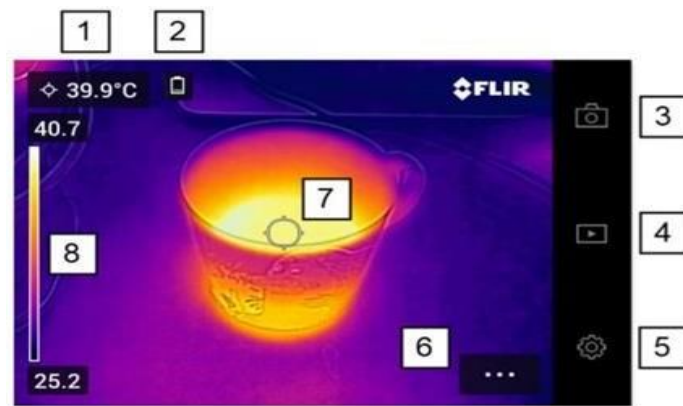


Fig.4.3 Feature of Thermal Camera from rear view



1. Result table.
2. Status icons.
3. Live view button.
4. Gallery button.
5. Settings button.
6. Menu button.
7. Spotmeter.
8. Temperature scale.

Fig.4.4 parameters of Thermal camera



Fig 4.5 Real time application of Thermal Camer

4.2.2 Thermal image over digital x-ray

Technology and Principle:

Thermal Imaging: Thermal imaging utilizes infrared radiation emitted by objects to create an image based on temperature variations. Thermal cameras detect and measure the infrared radiation emitted by objects, converting this data into a visible image where warmer areas are represented by brighter colors and cooler areas by darker colors. Thermal imaging is primarily used to visualize heat patterns and temperature differences in objects or living organisms.

X-ray Imaging: X-ray imaging, on the other hand, utilizes electromagnetic radiation in the form of X-rays to penetrate through tissues and create an image based on the differential absorption of X-rays by various structures within the body. Dense structures such as bones absorb more X-rays, appearing as white areas on the image, while softer tissues allow more X-rays to pass through, appearing as darker areas. X-ray imaging is commonly used to visualize internal structures, such as bones and organs, and detect abnormalities such as fractures, tumors, or foreign objects.

Applications

Thermal Imaging: In dentistry, thermal imaging can be used to detect temperature variations in oral tissues, aiding in the early detection of conditions such as inflammation, infection, or nerve damage.

X-ray Imaging: X-ray imaging is extensively used in medicine for diagnostic purposes, including but not limited to detecting fractures, assessing joint injuries, diagnosing dental problems, evaluating lung conditions, and screening for abnormalities such as tumors or foreign bodies. In dentistry, X-ray imaging techniques such as periapical, bitewing, and panoramic X-rays are commonly used for assessing dental health, identifying cavities, evaluating bone density, and planning treatments such as orthodontics or oral surgery.

Safety Considerations

Thermal Imaging: Thermal imaging involves the use of non-ionizing radiation (infrared radiation) and is considered safe for both the subject and the operator. It does not pose any known health risks and can be used repeatedly without concerns about radiation exposure.

X-ray Imaging: X-ray imaging utilizes ionizing radiation (X-rays), which can potentially cause cellular damage and increase the risk of cancer with repeated exposure. While X-ray imaging is generally safe when used appropriately and with proper shielding, precautions are necessary to minimize radiation exposure, particularly in vulnerable populations such as pregnant women and children.

4.2.3 Thermal cameras offer several advantages in dentistry, providing valuable insights and enhancing patient care.

Early Detection of Oral Health Issues: Thermal imaging can detect temperature variations in oral tissues, helping dentists identify potential issues such as inflammation, infection, or nerve damage at an early stage. This early detection enables prompt intervention and prevents the progression of dental problems.

Assessment of Blood Circulation: Thermal cameras can assess blood circulation in the gums, teeth, and surrounding tissues by detecting temperature changes. Poor circulation may indicate underlying conditions such as gum disease or compromised healing after dental procedures. Monitoring blood flow aids in treatment planning and evaluating treatment outcomes.

Identification of Oral Pathologies: Thermal imaging can aid in the detection of various oral pathologies, including oral cancers and temporomandibular joint (TMJ) disorders. By capturing thermal signatures of abnormal tissues, dentists can refer patients for further evaluation and early intervention, potentially improving treatment outcomes and prognosis.

Evaluation of Dental Restorations: Thermal imaging can assess the integrity of dental restorations such as fillings, crowns, and implants by detecting temperature irregularities around these structures. Temperature changes may indicate issues such as leakage, decay, or improper fit, prompting timely repairs or replacements to maintain oral health and function.

Non-Invasive Examination: Thermal imaging provides a non-invasive and painless method for evaluating oral health, particularly beneficial for patients who may experience anxiety or discomfort during traditional dental examinations. It allows dentists to gather valuable diagnostic information without the need for invasive procedures or radiation exposure.

Objective Documentation: Thermal imaging enables dentists to objectively document changes in oral tissues over time, providing a baseline for monitoring patients' oral health status and treatment progress. This visual documentation can aid in communication with patients, treatment planning, and interdisciplinary collaboration among healthcare providers.

Improved Patient Education: Thermal imaging can enhance patient education by visualizing temperature variations and explaining their significance about oral health conditions. Patients can better understand the importance of preventive measures, treatment options, and the potential consequences of untreated dental issues, leading to improved compliance and oral hygiene practices.

Research and Development: Thermal imaging technology contributes to dental research by facilitating studies on oral physiology, pathology, and treatment outcomes. Researchers can utilize thermal imaging data to investigate the efficacy of dental interventions, develop new diagnostic tools, and advance understanding of oral health-related conditions.

4.2.4 Thermal cameras offer several disadvantages in dentistry

Limited Diagnostic Specificity: Thermal imaging may lack the specificity needed to differentiate between various oral health conditions. While temperature variations can indicate potential issues, they do not provide detailed information about the nature or severity of the condition. As a result, additional diagnostic tools and procedures may be necessary to confirm diagnoses accurately.

Cost Considerations: Thermal imaging equipment can be expensive to acquire and maintain, which may pose financial challenges for dental practices, especially smaller ones or those operating on tight budgets. The initial investment in thermal imaging technology, along with ongoing maintenance and training costs, can be significant.

Interpretation Challenges: Interpreting thermal images requires specialized training and expertise. Dentists and dental professionals may require additional education to accurately analyze thermal patterns and integrate them into clinical decision-making. Misinterpretation of thermal images could lead to incorrect diagnoses or unnecessary treatments.

Influence of External Factors: External factors such as ambient temperature, humidity, and patient positioning can influence thermal imaging results. Changes in environmental conditions or patient factors may affect the accuracy and reliability of thermal measurements, potentially leading to misleading interpretations.

Limited Research and Validation: While thermal imaging shows promise as a diagnostic tool in dentistry, its widespread use is still relatively new, and there may be limited research and validation supporting its efficacy in various clinical applications. More studies are needed to establish standardized protocols, validate findings, and determine the optimal role of thermal imaging in dental practice.

Patient Acceptance and Comfort: Some patients may feel uncomfortable or apprehensive about undergoing thermal imaging procedures, particularly if they are unfamiliar with the technology or perceive it as invasive. Dentists must address patient concerns and provide clear explanations to ensure patient acceptance and cooperation during thermal imaging examinations.

Regulatory and Ethical Considerations: Dentists must adhere to regulatory guidelines and ethical standards when using thermal imaging technology in patient care. Compliance with data protection regulations informed consent requirements, and professional ethical codes is essential to safeguard patient privacy and uphold professional integrity.

Limited Availability and Accessibility: Thermal imaging equipment may not be readily available or accessible in all dental settings, particularly in rural or underserved areas. Limited access to thermal imaging technology may restrict its use and hinder its potential benefits for patients in these communities.

4.3 METHODOLOGY

The methodology describes the complete procedure from surveying of literature to comparative analysis of the results obtained from Thermal cameras and Digital X- ray images. The given figure shows the methodological framework.

Initial Patient Data Collection:

The first step of the survey involves the visitation of patients to Sathyabama Dental Hospital and College. During this phase, meticulous records of patient data are compiled. This includes comprehensive information such as the patient's name, age, gender, and other pertinent details relevant to their dental health.

Collection of Patient Samples:

Following the initial data collection, the focus shifts towards gathering patient samples. This is accomplished through two distinct methods:

Thermal Camera Imaging: Utilization of a thermal camera to capture thermal images of the patient. This allows for the visualization of temperature differentials across oral structures.

Digital X-ray Imaging: Various techniques such as RVG (Radiovisiography), OPG (Orthopantomography), and IOPA (Intraoral Periapical Radiography) are employed to acquire digital X-ray images. These X-rays provide detailed insights into the internal structures of the oral cavity

Comparison of Imaging Modalities:

Following the acquisition of thermal images and digital X-rays, a meticulous comparative analysis is undertaken by hospital staff. This involves a side-by-side evaluation of thermography images against digital X-rays. The primary objective of this step is to identify any discordances or abnormalities between the two imaging modalities.

Result Analysis and Conclusion:

Based on the comprehensive dataset comprising patient information, thermal images, and digital X-rays, the hospital proceeds to draw conclusive insights. This phase involves an in-depth analysis of the collected data, which may culminate in several outcomes:

Diagnosis of dental conditions or abnormalities.

Formulation of tailored treatment plans based on the identified issues.

Recommendations for further investigative procedures, if necessary.

Literature survey



Visiting Sathyabama Dental Hospital



Recording the patient's data (like Name, Age, Gender, etc.) Physical data includes Patient complaint, Findings, Diagnosis (Provisional, Radiography) Thermography findings, and Final Diagnosis



Collecting patient samples using thermal camera and digital X-ray (RVG, OPG, IOPA)



Analyzing the thermography images using Convolution Neural Networks (pre-trained networks)



Results and conclusion

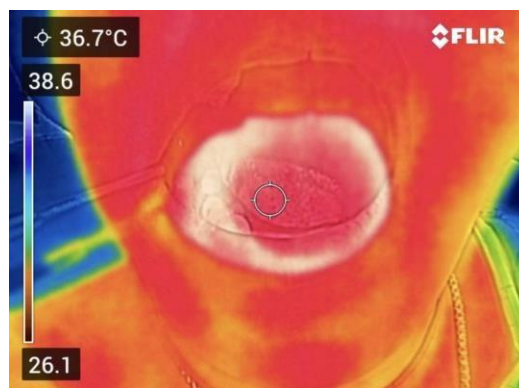
• ***METHODOLOGICAL FRAMEWORK***



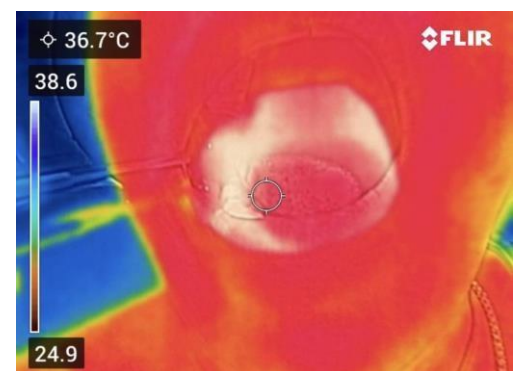
(a)



(b)



(c)



(d)

Fig 4.6 Normal image (a), X-Ray (b), Thermal images (c)&(d) of affected patient no.1

COMPLAINT: Patient complaints pain in her upper right back tooth region for past 2 month

CLINICAL FINDINGS:

- Number of teeth: 31
- Grossly decayed irt 18
- Partially erupted irt 48

PROVISIONAL DIAGNOSIS:

- Dental caries with Apical Periodontitis irt 18
- Generalized chronic gingivitis
- Impacted teeth irt 48

RADIOGRAPHY:

Radiolucency involving enamel, dentin and pulp with widening of periodontal ligament space suggestive of dental carries with Apical Periodontitis irt 18.

FINAL DIAGNOSIS:

- Dental caries with Apical Periodontitis irt 18

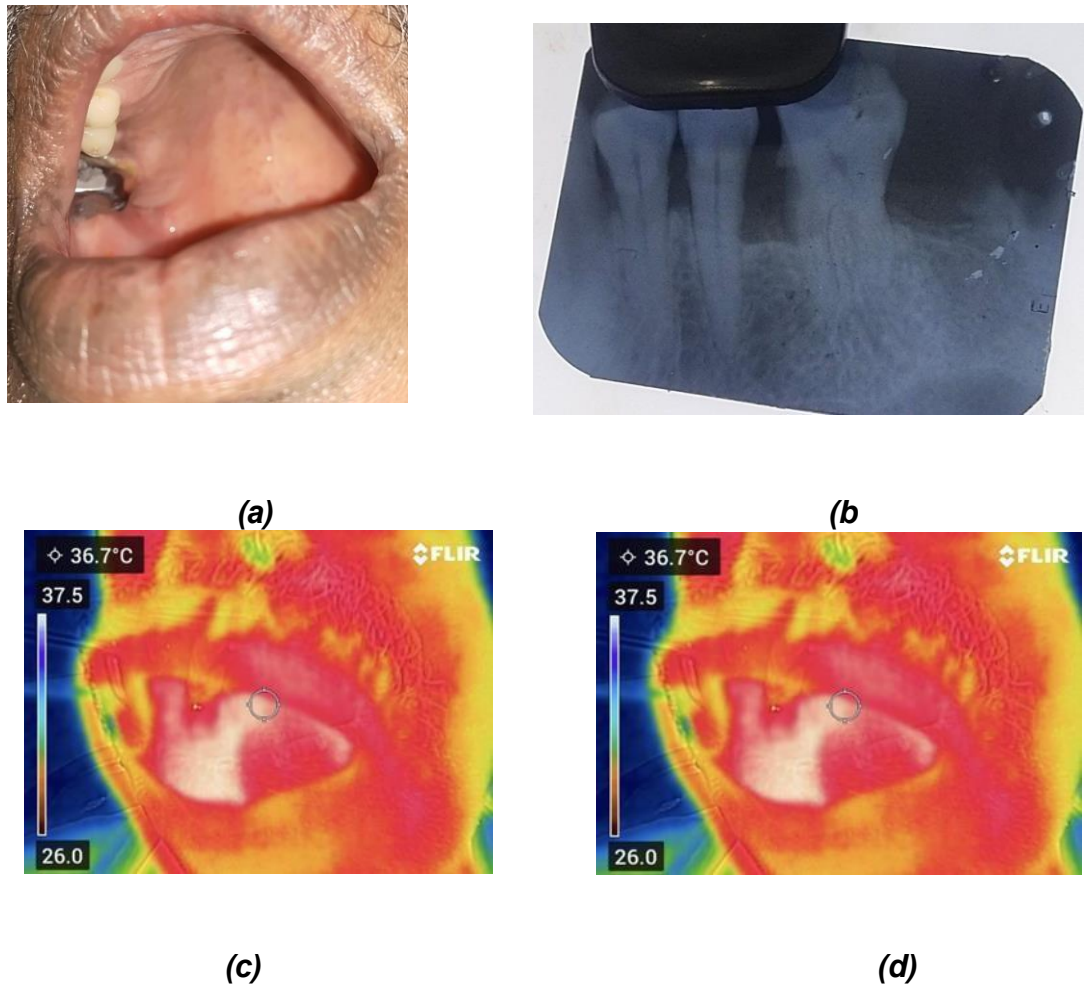


Fig 4.7 Normal image (a), X-Ray (b), Thermal images (c)&(d) of affected patient no.2

COMPLAINT: Patient complaints of missing tooth and wants to replace it.

CLINICAL FINDINGS:

- Number of teeth: 27
- Root stump: 28,27
- Restoration: 17
- Missing - 16
- Stains & Calculus - moderate
- Recession - 31,32,41,42

PROVISIONAL DIAGNOSIS:

- Chronic irreversible pulpitis irt 28,27
- Partially edentulous irt 16
- Localised Periodontitis irt 31,32,41,42

RADIOGRAPHY: IOPA of 27,28 reveals loss of coronal tooth structure with presence of radicular portion suggestive of chronic irreversible pulpitis irt 27,28

FINAL DIAGNOSIS:

- Partially edentulous irt 16
- Localised Periodontitis irt 31,32,41,42



(a)



(b)



(c)



(d)

Fig 4.8 Normal image (a), X-Ray (b), Thermal images (c)&(d) of affected patient no.3

COMPLAINT: Patient complaints of pain for the past one day and black discoloration of upper front tooth region and wants to clean the teeth

CLINICAL FINDINGS:

- No of teeth: 18
- Dental carries: 11,13,14,15,21,25,33,34,36,47
- Missing: 12,17,18,24,26,27,28,33,34,36
- Restored: 37,38,46,48
- Stain: mild
- Calculus: moderate
- Root stump: 16

PROVISIONAL DIAGNOSIS: Dental carries 11,13,14,15,21,25,33,34,36,47
Extraction irt 16
Replacement irt 28,37,38,48

RADIOGRAPHY: IOPA Reveals ill define Radiolucency at the apex of the root suggestive of periapical abscess

FINAL DIAGNOSIS: Dental carries with periapical abscess irt 21



(a)



(b)



(c)



(d)

Fig 4.9 Normal image (a), X-Ray (b), Thermal images(c)&(d) of affected patient no.4

COMPLAINT: Patient complaints of shaking teeth in her lower front teeth region for past 2 years and wants to remove it

CLINICAL FINDINGS: Number of teeth 23
Mobility irt - 31,41
Generalized grade - 2 mobility
Grossly decayed irt 11,23,34
Root stump irt 14,15,38,47,37
Dental carries irt 21,22,26,45,46,12

PROVISIONAL DIAGNOSIS: Generalized chronic Periodontitis
Chronic irreversible pulpitis irt 11,23,34,14,15,38,47
Dental carries irt 21,22,26,45,46

RADIOGRAPHY: OPG reveals loss of coronal root structure with presence of radicular portion irt 14,15,38,47,35

OPG also reveals Generalized bone loss

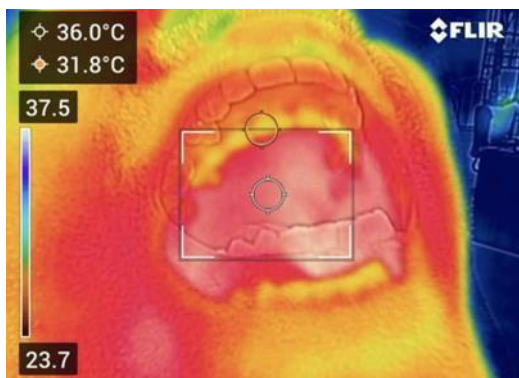
FINAL DIAGNOSIS: Generalized chronic Periodontitis
Chronic irreversible pulpitis irt 11,23,34,14,15,38,47



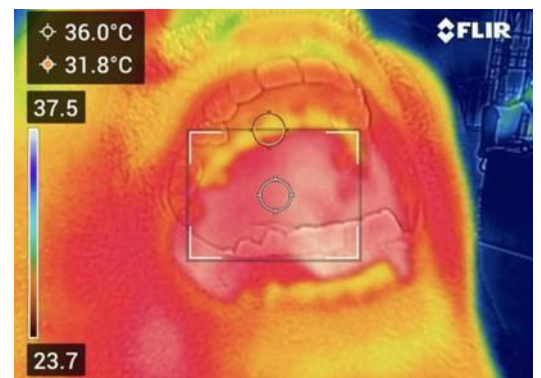
(a)



(b)



(c)



(d)

Fig 4.10 Normal image (a), X-Ray (b), Thermal images (c)&(d) of affected patient no.5

COMPLAINT: Patient complaints of broken restoration and wants to fill the tooth

CLINICAL FINDINGS:

- Number of teeth: 30
- Stain & Calculus - mild
- Missing - 15,27
- Broken tooth - 25 (Dental caries)
- Restoration: 26

PROVISIONAL DIAGNOSIS: Fractured tooth irt 25
Partially edentulous irt 15,27

RADIOGRAPHY: IOPA of 25 reveals enamel, dentin, and distoproximal caries with adjacent radiolucency involving pulp chamber suggestive of I'll define periapical radiolucency irt 25

FINAL DIAGNOSIS: Secondary carries with periapical lesion

PATIENT DETAILS

- 1. PATIENT NAME**
- 2. OP NUMBER**
- 3. DATE**
- 4. AGE**
- 5. GENDER**
- 6. MOBILE NUMBER**
- 7. COMPLAINT**
- 8. CLINICAL FINDINGS**
- 9. PROVISIONAL DIAGNOSIS**
- 10. RADIOGRAPHY**
- 11. THERMOGRAPHY FINDINGS**
- 12. FINAL DIAGNOSIS**

4.3.1 Deep learning Model

Detecting oral diseases from oral thermal images using deep learning involves a sophisticated approach that leverages the capabilities of artificial intelligence to analyze and interpret medical images. This technology can greatly enhance the precision and efficiency of diagnosing oral health conditions. Steps involved in creating and performing a deep learning model.

1. Data Collection

Patient Consent and Ethics: Outline the ethical considerations and patient consent requirements.

Image Acquisition: Describe the thermal imaging equipment and settings used to capture the images. Explain how the images are standardized and the parameters ensured for consistency.

•

2. Preprocessing of Data:

The preprocessing steps necessary for preparing the thermal images for analysis:

Noise Reduction: Techniques used to clean the images of any artifacts or noise.

Normalization: Standardizing the intensity scales of thermal images.

Augmentation: Methods such as rotation, scaling, and flipping to increase the dataset size and variability.

Deep Learning Model Development

Outline the development of the deep learning model:

Model Architecture: Describe the architecture of the neural network (e.g., CNN, ResNet, etc.). Discuss why a particular model was chosen based on its performance in similar tasks.

Training: Detail the training process, including the division of data into training, validation, and test sets. Mention the hyperparameters, learning

rate, and loss functions used.

Validation: Explain the procedures for validating the model, including cross-validation techniques if used.

Performance Evaluation

Discuss how the model's performance is evaluated:

Metrics: Include metrics such as accuracy, precision, recall, F1 score, and AUC-ROC curve.

Comparison with Traditional Methods: Provide a comparison of model performance against traditional diagnostic methods.

Error Analysis: Discuss any misclassifications or errors made by the model and potential reasons.

4.3.2 Resnet-18

ResNet-18 is a version of the Residual Network (ResNet) architecture that is commonly used in deep learning for tasks like image recognition and classification. Developed by Kaiming He and colleagues in their seminal paper, "Deep Residual Learning for Image Recognition" (2015), ResNet models have become popular due to their ability to train very deep networks effectively. The "18" in ResNet-18 refers to the number of layers that have weights; this version of ResNet is relatively shallow compared to other versions like ResNet-34, ResNet-50, ResNet-101, and ResNet-152.

:

Overview of ResNet-18

ResNet-18 architecture includes several stacked residual blocks. These blocks help mitigate the vanishing gradient problem in deep neural networks by introducing skip connections, or shortcuts that allow the gradient to flow through many layers without attenuation. Each residual block typically consists of two layers in ResNet-18, with each layer containing a 3x3 convolution, batch normalization, and a ReLU activation function.

Using ResNet-18 for Oral Disease Detection

Data Preparation: For ResNet-18 to be effective, your input images (thermal images of the oral cavity) must be preprocessed:

- **Resize Images:**
- ResNet typically uses input images of size 224x224. Ensure your images are resized accordingly.
- **Normalization:** Normalize pixel values to match the input characteristics for which ResNet was originally trained (usually with a mean and standard deviation computed across all ImageNet training images).
-

Model Adaptation:

- **Transfer Learning:** Since ResNet-18 is pretrained on ImageNet, which includes a variety of natural images but not thermal images, you might utilize transfer learning. Here, you could either retrain the entire network with your specific dataset or fine-tune the later layers while freezing the earlier layers.
- **Output Layer:** Adjust the final fully connected layer to match the number of classes in your specific problem (e.g., types of oral diseases you are detecting).
-

Training the Model:

- **Loss Function:** Depending on your task (binary or multi-class classification), choose an appropriate loss function, such as cross-entropy.
- **Optimizer:** Use an optimizer like Adam or SGD with momentum, tuning the learning rate and decay parameters based on your dataset.
- **Data Augmentation:** To improve model robustness, consider using data augmentation techniques like rotations, translations, and scaling on your

training dataset.

Model Evaluation:

- Validation Techniques: Use techniques like k-fold cross-validation to evaluate the model's performance and ensure that it generalizes well to unseen data.
- Performance Metrics: Measure the model's accuracy, precision, recall, F1-score, and analyze the confusion matrix to understand its strengths and weaknesses in classifying different diseases.

Interpretability and Fine-tuning:

- Analyze misclassifications and feature importance to understand how the model is making its decisions. This step is crucial for medical applications where interpretability is important.
- Based on initial results, consider fine-tuning the architecture or training procedure — adjusting the number of layers frozen during transfer learning, or experimenting with different augmentation strategies.

4.3.3 Resnet-50

ResNet-50 is a variant of the ResNet architecture, which is widely used in the field of deep learning for tasks involving image recognition and classification. The "50" in ResNet-50 refers to the number of layers in the network that have trainable weights, totaling 50 layers. This architecture is part of the family of Residual Networks that was introduced by Kaiming He and colleagues in the seminal paper "Deep Residual Learning for Image Recognition" (2015). ResNet architectures are particularly known for their use of residual connections, which are key to enabling the training of very deep networks.

Architecture Details ResNe-50 consists of:

Convolutional Layers: It begins with an initial 7x7 convolutional layer with 64 filters, followed by a max pooling layer.

Residual Blocks: The core of the network includes 16 residual blocks. Each block typically consists of three layers:

The first and third layers in each block are 1x1 convolutions, designed for dimensionality reduction and then restoration. This setup helps in reducing the computational complexity.

The second layer is a 3x3 convolution, which is the main feature extractor within the block.

Each of these convolutions is followed by batch normalization and ReLU activation.

Skip Connections:

Each residual block features a skip connection that bypasses the main layers (the three convolutional layers) by performing an identity mapping. If the input and output dimensions differ, the skip connection uses a 1x1 convolution to adjust dimensions.

Global Average Pooling: Towards the end, the network uses a global average pooling layer to reduce each feature map to a single value.

Fully Connected Layer: This is followed by a fully connected layer that outputs to the final classification layer.

Key Features

Deep Network with Manageable Complexity: Despite having 50 layers, the use of global average pooling and 1x1 convolutions manages the complexity efficiently.

Skip Connections: These are critical in ResNet-50 as they allow gradients to flow directly through the network without vanishing, which is a common problem in very deep networks. This design supports effective training of deep networks by providing paths for gradients to flow through the architecture.

Versatility: ResNet-50 is pre-trained on millions of images from the ImageNet database, making it robust and versatile for a wide range of image recognition tasks. It performs exceptionally well as a starting point for many computer vision tasks due to its deep feature extraction capabilities.

Applications

ResNet-50 is highly popular in various applications beyond simple image classification, including:

- Object Detection:
 - As part of systems like Faster R-CNN or YOLO, where ResNet can serve as a feature extractor.
- Image Segmentation: In architectures such as U-Net where a variant of ResNet may be used as a backbone.
- Transfer Learning: Due to its robust pre-training, it's commonly adapted to specific tasks (including medical image analysis) by fine-tuning the network on a smaller, task-specific dataset.

In medical image analysis, and specifically in applications like detecting oral diseases from thermal images, ResNet-50 offers a powerful, deep feature-extraction mechanism that can be fine-tuned to handle the peculiarities of medical imaging data, even when it differs significantly from the natural images used in its initial training.

4.3.4 Darknet-53

Darknet-53 is a neural network architecture that serves as the backbone for YOLOv3, one of the versions of the You Only Look Once (YOLO) object detection system. YOLO is renowned for its speed and accuracy in detecting objects in real-time, making it a popular choice for applications requiring real-time processing.

Overview of Darknet-53:

Darknet-53 is primarily designed for object detection tasks and is characterized by its depth and efficiency. It consists of 53 convolutional layers, hence the name "Darknet-53". It was introduced with YOLOv3 by Joseph Redmon and Ali Farhadi in their 2018 paper titled "YOLOv3: An Incremental Improvement".

Architecture Details:

- *Convolutional Layers:* Darknet-53 contains 53 convolutional layers which are used for feature extraction. These layers use a variety of kernel sizes, primarily 1x1 and 3x3. The 1x1 convolutions are used to reduce the feature

space dimensionality, thereby compressing the features, whereas the 3x3 convolutions help in expanding the feature space and capturing complex features.

- *Residual Blocks:* The architecture utilizes residual blocks similar to those found in the ResNet family of architectures. These blocks help prevent the vanishing gradient problem by allowing gradients to flow through a shortcut connection that skips one or more layers.
- *Batch Normalization:* Each convolutional layer is followed by batch normalization, which stabilizes learning by normalizing the input layer by adjusting and scaling activations.
- *Leaky ReLU Activation:* Unlike many other architectures that use ReLU, Darknet-53 uses the Leaky ReLU activation function. This variant of ReLU allows a small, non-zero gradient when the unit is not active and provides a range for the negative axis, potentially increasing the range of functionalities it can model.

Performance Characteristics:

- *Efficiency and Speed:* Darknet-53 is highly efficient, optimized for performance, and faster than its predecessors or many other contemporary architectures due to fewer floating-point operations (FLOPs) and an effective design that maximizes throughput on hardware.
- *Accuracy:* While designed for speed, Darknet-53 does not compromise much on accuracy, making it suitable for real-time applications where both speed and accuracy are critical.

Applications

- *Object Detection:* It's the backbone for YOLOv3, making it suitable for real-time object detection in videos, including for applications like surveillance, vehicle detection, and activity recognition.
- *Transfer Learning:* Given its robust feature extraction capabilities, it can be adapted to new, less data-rich applications by fine-tuning the pre-trained model on a new dataset.

In contexts other than real-time object detection, like medical imaging or oral disease detection from thermal images, Darknet-53 could theoretically be adapted, although it isn't typically used in these areas. The choice of using Darknet-53 for such applications would depend on specific requirements for speed and the type of feature representations needed for the task. For deep learning tasks involving complex and high-resolution images where detailed spatial hierarchies are important (such as in medical imaging), architectures like ResNet may be more traditionally appropriate due to their depth and complexity, which handle nuanced features effectively. However, Darknet-53 could provide an interesting alternative if processing speed is also a critical factor.

4.3.5 Darknet-19

Darknet-19 is a convolutional neural network (CNN) architecture that was introduced as part of the YOLOv2 (You Only Look Once, version 2) object detection system. It was developed by Joseph Redmon, et al., and outlined in the 2016 paper titled "YOLO9000: Better, Faster, Stronger." This model is an iteration of the original YOLO model, improving upon its predecessor by being both faster and more accurate, all the while maintaining the ability to run in real-time.

Architecture Details of Darknet-19:

Darknet-19 is named for its 19 convolutional layers, but the total number of layers including pooling layers amounts to more than 19. Here are the key features of this architecture:

- **19 Convolutional Layers:** The architecture features 19 convolutional layers which use 3x3 and 1x1 filters. The 1x1 filters reduce the feature space dimensionality, thereby acting as bottleneck layers to compress the features before they are expanded again by 3x3 filters.
- **Batch Normalization:** Following the introduction in newer neural network designs, each convolutional layer in Darknet-19 is followed by batch normalization, which helps in stabilizing the learning process by normalizing

the activations. This leads to faster convergence and reduces the sensitivity to network initialization.

- *Max Pooling*: The network uses max pooling strategically after certain convolutional layers to reduce the spatial dimension of the feature maps, thereby reducing the computational burden and helping in extracting robust features.
- *Leaky ReLU Activation*: Each convolutional layer is followed by a leaky version of a Rectified Linear Unit (Leaky ReLU), which allows a small gradient when the unit is inactive and thus helps the network learn faster.
- *Passthrough Layer*: Unique to the YOLOv2 architecture, Darknet-19 uses a passthrough layer from an earlier layer to the later layers to fine-tune the features extracted by the network. This helps in improving the detection of small objects, a feature borrowed from the concept of skip connections in ResNet.

Performance Characteristics

- *Efficiency*: Darknet-19 is designed for efficiency, optimizing computational resource use without significant sacrifices in accuracy. This makes it particularly well-suited for applications on devices with limited computational power.
- *Speed*: It is optimized for real-time performance, making it suitable for applications that require fast object detection capabilities, such as video surveillance and robotics.
- *Accuracy*: While being fast, it still maintains a high level of accuracy compared to other real-time detectors available at the time of its introduction.

Applications

- *Real-time Object Detection*: The primary application of Darknet-19 is as the backbone for YOLOv2 in real-time object detection systems. It is capable of detecting objects rapidly and accurately across a wide range of conditions and object types.
- *Embedded Systems*: Due to its efficiency and speed, Darknet-19 is also well-suited for deployment in embedded systems or on edge devices for tasks such as autonomous driving, drone operation, and mobile applications.

Darknet-19 is an effective and efficient architecture primarily used in the context of real-time object detection. Its design principles focus on speed and accuracy, leveraging innovations such as batch normalization, leaky ReLU activations, and architectural optimizations to deliver top-notch performance in practical applications.

4.3.6 VGG-16

VGG-16 is a widely-used convolutional neural network architecture named after the Visual Geometry Group from Oxford, who developed it. It was first introduced in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition" by Karen Simonyan and Andrew Zisserman in 2014. The architecture was remarkable at the time for its depth; with 16 convolutional layers, it was considerably deeper than other networks used for similar tasks.

Architecture Details of VGG-16

- *16 Layers with Weights:* VGG-16 features a total of 16 layers that have weights; this includes 13 convolutional layers and 3 fully connected layers.
- *Convolutional Layers:* The convolutional layers use 3x3 filters with a stride of 1 pixel; this small filter size is used consistently throughout the entire network, which was one of the key insights of the architecture. It allows for the capture of more fine-grained detail in the input images.
- *Fixed Padding:* The convolutional layers use padding to preserve the spatial resolution of the image throughout the network, allowing for deep architectures without reducing the size of the output feature maps too quickly.
- *Max Pooling:* Max pooling is performed over a 2x2 pixel window, with a stride of 2, to reduce the dimensionality of the feature maps after certain convolutional layers.
- *Fully Connected Layers:* After the convolutional layers, three fully connected layers follow. The first two have 4096 channels each, and the third performs 1000-way classification (matching the number of classes in the ImageNet challenge) and uses a softmax function to output probabilities of the different classes.

- *ReLU Activation:* The Rectified Linear Unit (ReLU) activation function is used throughout the network to add non-linearity to the decision function and gradients, allowing the model to learn more complex patterns.

Key Features and Design Choices

- *Depth:* One of the distinguishing features of VGG-16 is its depth. More layers allow the network to learn more complex features at various levels of abstraction.
- *Uniform Architecture:* The use of the same filter size and stride throughout the network simplifies the architecture, making it easier to scale and modify.
- *Large Number of Parameters:* VGG-16 has a very high number of parameters (over 138 million), which makes it computationally intensive to train and can lead to overfitting on smaller datasets.

Applications

- *Image Classification:* VGG-16 has been widely used for image classification tasks. Its architecture is effective at learning hierarchical features, which are useful for this purpose.
- *Transfer Learning:* Due to its performance on ImageNet and its general ability to capture useful features from images, VGG-16 is often used as a pre-trained model for transfer learning in other vision tasks, such as object detection and image segmentation.
- *Feature Extraction:* Features extracted from various layers of VGG-16 are often used for other applications beyond classification, including content-based image retrieval and style transfer.

Despite its older design and higher computational cost compared to newer architectures like ResNet, EfficientNet, or transformers, VGG-16 remains a popular choice, especially in educational contexts and baseline comparisons, due to its simplicity and the robustness of the features it can learn.

4.3.7 Squeezenet

SqueezeNet is a convolutional neural network architecture that achieves AlexNet-level accuracy on the ImageNet dataset with a significantly reduced number of parameters and model size. It was introduced by researchers from DeepScale, UC Berkeley, and Stanford University in the paper titled

"SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size,".

Key Features of SqueezeNet

1. *Reduced Model Size:* One of the principal achievements of SqueezeNet is its small model size. By design, it uses fewer parameters than other architectures that achieve similar levels of accuracy. This makes it highly efficient for storage, which is particularly valuable for deploying deep learning models on devices with limited memory and processing power, such as mobile devices or embedded systems.
2. *Architectural Innovations:* SqueezeNet introduces several architectural strategies to reduce the number of parameters without sacrificing accuracy:
 - *Fire Modules:* These are the building blocks of SqueezeNet, consisting of a squeeze layer (which has only 1x1 filters) followed by an expand layer that has a mix of 1x1 and 3x3 filters. The squeeze layer reduces the depth of the feature maps, thus decreasing the number of inputs to the expand layer, which in turn reduces the computational complexity.
 - *Decreased Use of 3x3 Filters:* The network primarily uses 1x1 filters, which require fewer parameters than 3x3 filters. Where 3x3 filters are used, they are applied to a reduced number of input channels.
 - *Delayed Downsampling:* SqueezeNet delays downsampling to late in the network, allowing convolutional layers to operate on feature maps with a larger spatial footprint. This can help to increase the accuracy of the network.

Architecture Details

SqueezeNet consists of a series of Fire modules interspersed with max-pooling layers. The typical layout includes:

- An initial convolution layer.
- Several Fire modules.
- Intermediate max-pooling layers placed strategically to reduce spatial dimensions periodically.

A final conv layer followed by global average pooling to predict the classes.

Performance and Applications

- *Efficiency and Speed:* With its compact architecture, SqueezeNet is very efficient, requiring less bandwidth for data transfer, which can be crucial for real-time applications.
- *Versatility:* Its small size and the possibility of further compression without significant loss in performance make SqueezeNet versatile for both server-side and edge device deployments.
- *Transfer Learning and Feature Extraction:* Similar to other convolutional networks, SqueezeNet can be used as a feature extractor for various vision-based tasks, and its layers can serve as a foundation for transfer learning in different contexts.

SqueezeNet is particularly useful in environments where memory and data bandwidth are limited. It's ideal for mobile applications, embedded systems, and web applications where deploying smaller models may be beneficial for rapidloading and processing times. Additionally, despite the small size, the model does not sacrifice much in terms of accuracy, making it a practical choice for many image recognition tasks.

CHAPTER 5

RESULT AND DISCUSSION

5.1 Performance of Deep Learning Models

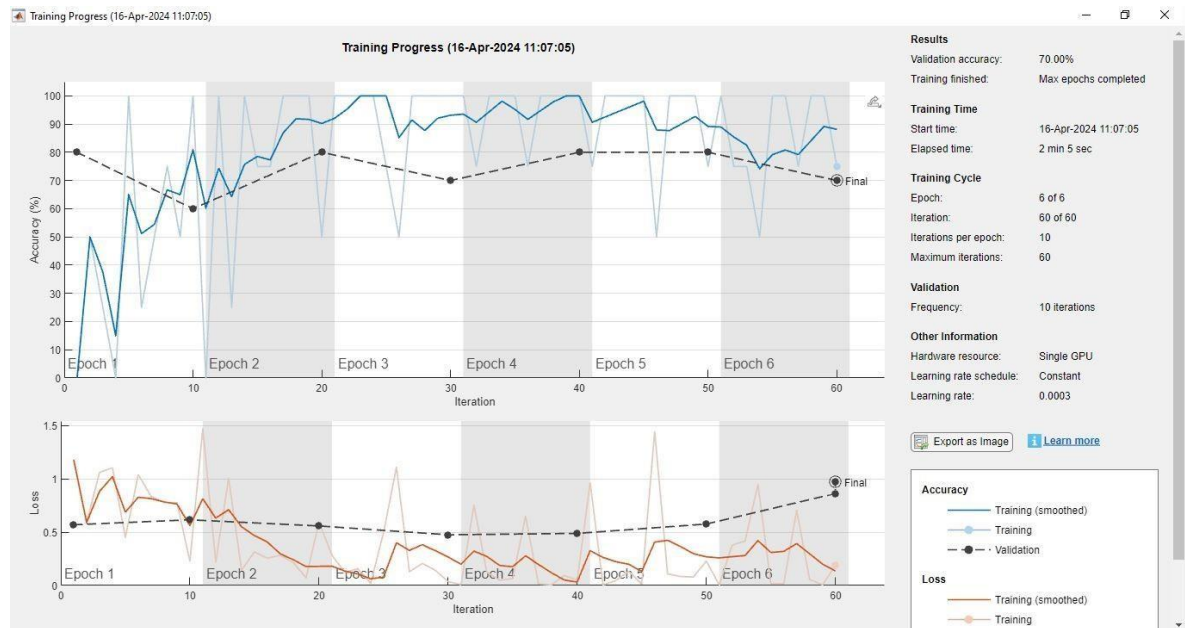


Fig 5.1 Graph of Resnet-50 training

1. **Accuracy Graph:** The top graph displays the accuracy of the model over six epochs. The blue line represents the accuracy on the training data, smoothed to provide a clearer trend, while the black line represents the accuracy on the validation data. The increasing trend in both lines indicates that the model is learning from the data, as both training and validation accuracies are generally improving over time. This is a positive indication of the model's performance.
2. **Loss Graph:** The bottom graph illustrates the loss of the model over the same six epochs. The orange line represents the loss on the training data, smoothed for clarity, while the dashed black line represents the loss on the validation data. The decreasing trend in both lines indicates that the model's performance is improving over time, as the loss decreases. This suggests that the model is making fewer mistakes and becoming more accurate in its predictions.

3. Training Progress Details:

- **Validation Accuracy:** The validation accuracy of the model is reported as 50.00%. This indicates the proportion of correctly predicted labels on a separate validation dataset, providing an assessment of the model's generalization performance.
- **Training Status:** The training process has been completed, reaching the maximum specified number of epochs. In this case, 6 out of 6 epochs were completed, with a total of 60 iterations (or batches) processed.
- **Hardware Resource:** The model was trained using a single GPU, indicating the hardware resources utilized during training.
- **Learning Rate Schedule:** The learning rate schedule used during training is described as "Constant," meaning that the learning rate remained the same throughout the training process.
- **Learning Rate:** The learning rate used during training is reported as 0.003. The learning rate is a hyperparameter that controls the stepsize during the optimization process and affects the rate at which the model learns from the data.

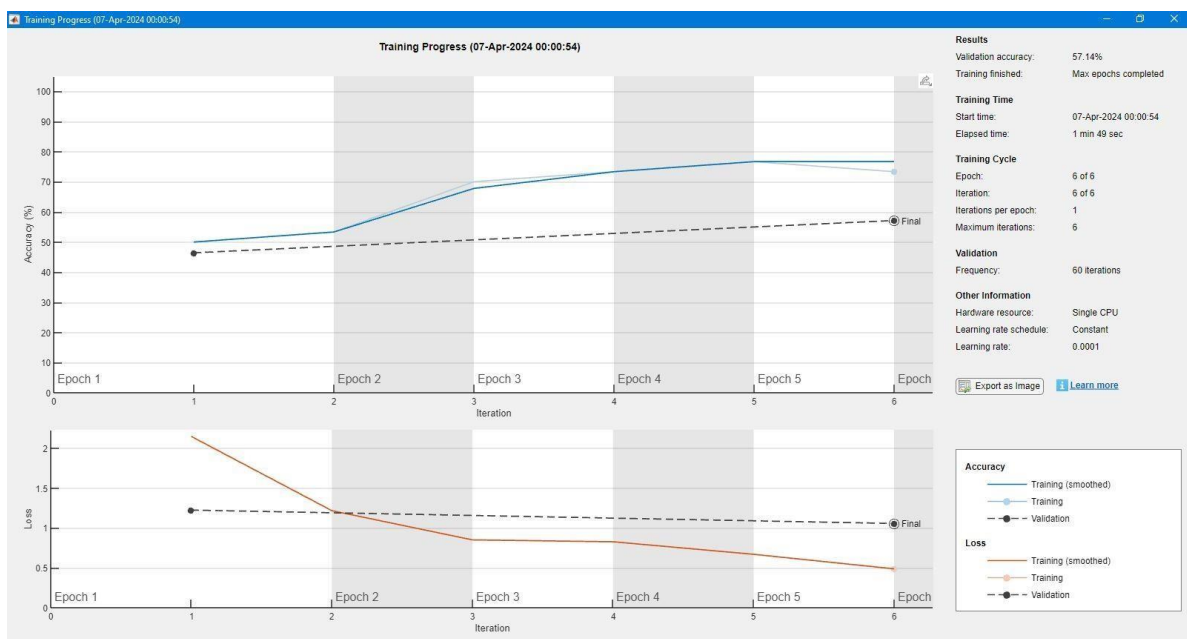


Fig 5.2 Graph of Resnet-18 training

- **Accuracy Graph:** It features two lines representing training (smoothed) and validation accuracy, with markers for each epoch. The accuracy reaches up to 90.00%.
- **Loss Graph:** Below the accuracy graph, there's a loss graph that plots the loss value over iterations for both training (smoothed) and training. This graph also has markers for each epoch.
- **Results Section:** On the right side of the image, there's a panel that provides the following details:
 - Validation Accuracy: 90.00%
 - Training Status: Training has finished, and the maximum number of epochs has been completed.
 - Training Cycle:
 - Epoch: 6 of 6
 - Iteration: 50 of 50
 - Iterations per Epoch: 10
 - Maximum Iteration: 60
 - Validation Frequency: Every 10 iterations

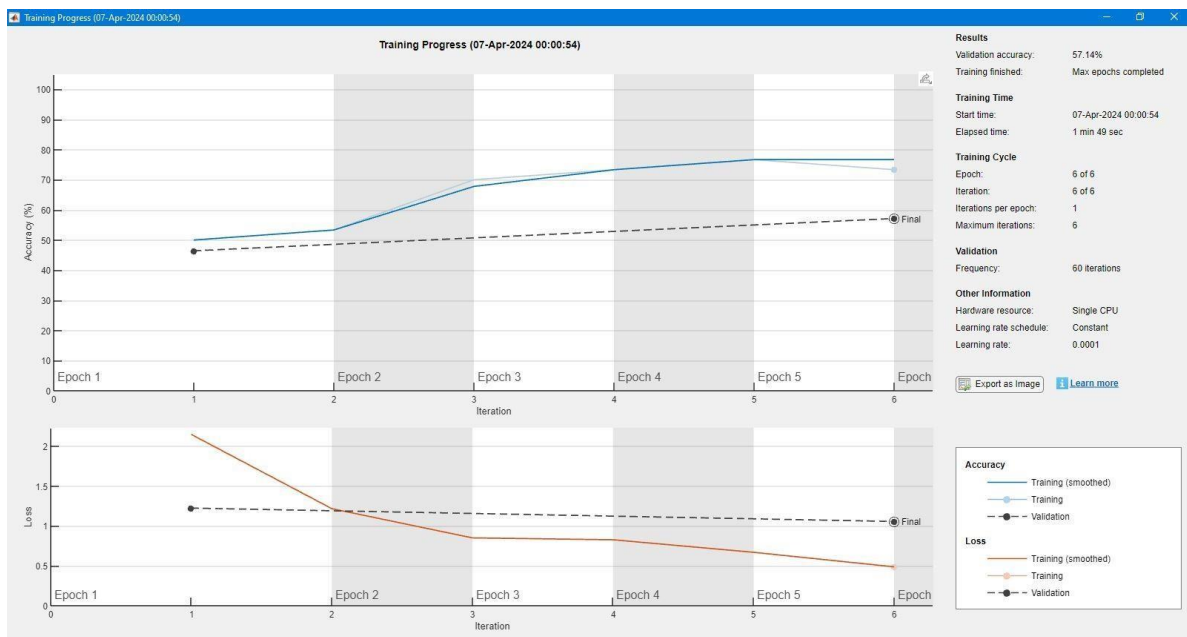


Fig 5.3 Graph of Darknet-19 training

- **Accuracy and Loss Graphs:** The image features two main graphs. The first graph tracks the accuracy (%) of the model over 5 epochs, with separate lines for training (blue) and validation (black). The second graph shows the loss for both training (orange) and validation (black), decreasing over the same epochs.
- **Training Progress Details:**
- **Validation Accuracy:** 67.14%
- **Training Time:** The model training started on 07-April-2024 at 00:01:53 and ran for 11 minutes and 49 seconds.
- **Training Cycle:** The training completed 5 epochs with 6 iterations per epoch, totaling 30 maximum iterations.
- **Validation Frequency:** Every 50 iterations.
- **Other Information:** The training used a single CPU, a cyclical learning rate schedule, and a learning rate of 0.0010.

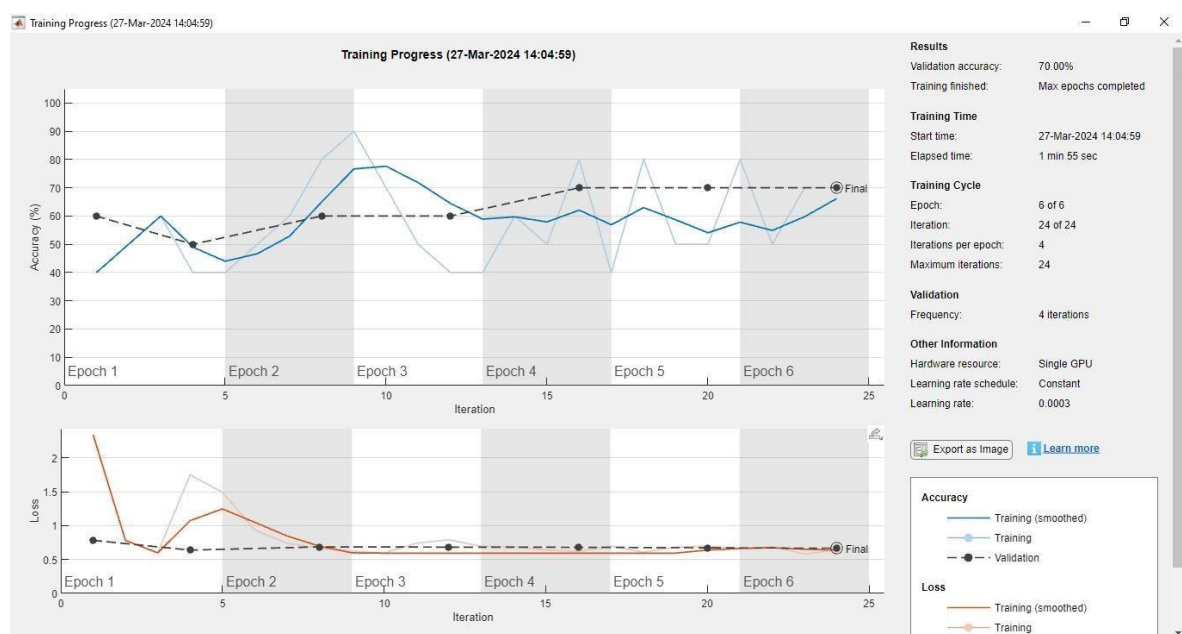


Fig 5.4 Graph of Squeezenet training

- **Accuracy Graph:** The top graph shows the model's accuracy over six epochs, with separate lines for training (smoothed) in blue and validation in black. The accuracy peaks at 70.00%.
- **Loss Graph:** The bottom graph displays the loss over the same epochs, with lines for training (smoothed) in orange and training in a dashed black line. The loss decreases over time, which is typical during the training process.
- **Training Progress Details:**
- **Validation Accuracy:** 70.00%

- Training Cycle:
- Epoch: 6 of 6
- Iteration: 24 of 24
- Iterations per Epoch: 4
- Maximum Iterations: 24
- Validation Frequency: Every 4 iterations

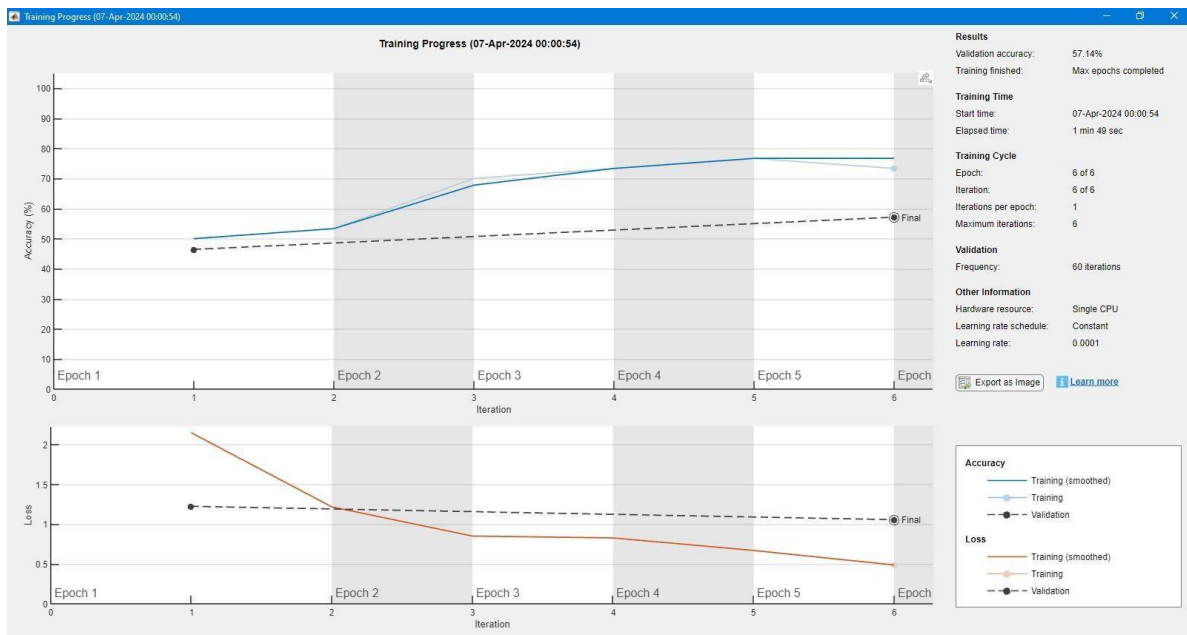


Fig 5.5 Graph of VGG-16 training

- **Accuracy and Loss Graphs:** There are two line graphs displayed.
 - The top graph shows the training accuracy increasing over time, represented by a blue line across epochs 1 to 6.
 - The bottom graph depicts the training loss decreasing over time, indicated by an orange line, also across epochs 1 to 6.
- **Training Progress Information:**
- Validation accuracy is noted as 67.14%, and it mentions that the training is finished after six epochs.
- The Training Time section lists an elapsed time of 11 minutes and 4 seconds, with no remaining time as the training has been completed.
- Training Cycle details include the current epoch (6 of 6), iteration (6 of 6), iterations per epoch (1), maximum iterations (6), and validation frequency (every 50 iterations).
- Other Information notes the hardware used (Single CPU) and the learning rate (0.001)

CHAPTER - 6

SUMMARY AND CONCLUSION

Summary

Thermal imaging has emerged as a promising non-invasive tool for the early detection and monitoring of oral diseases. This innovative technique offers several advantages, including its ability to provide real-time, quantitative data and its non-invasiveness, making it suitable for routine clinical use. By capturing temperature patterns of oral tissues, thermal imaging can identify changes indicative of underlying pathologies such as periodontal diseases, dental caries, and oral cancer. Moreover, thermal imaging has the potential to complement conventional diagnostic methods by offering additional insights into the extent and severity of oral diseases. While further research is needed to standardize imaging protocols and validate its clinical utility, the integration of thermal imaging into routine dental practice holds promise for improving early detection, facilitating timely intervention, and enhancing patient outcomes in the management of oral diseases.

Conclusion

In conclusion, thermal imaging represents a valuable adjunctive tool for the assessment of oral diseases. Its non-invasive nature, rapidity, and ability to provide real-time data make it a promising modality for routine clinical use. By capturing temperature variations in oral tissues, thermal imaging can aid in the early detection and monitoring of various oral pathologies, thus facilitating timely intervention and improving patient outcomes. However, further research is warranted to establish standardized imaging protocols, validate diagnostic criteria, and evaluate the cost-effectiveness of thermal imaging in oral health care settings. With continued advancements in technology and increased awareness among dental professionals, thermal imaging has the potential to revolutionize oral disease diagnosis and management, ultimately leading to better oral health outcomes for patients worldwide.

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