Received: 8 October 2023 | Revised: 14 November 2023 | Accepted: 18 December 2023 | Published online: 19 December 2023

RESEARCH ARTICLE

Archives of Advanced Engineering Science

yyyy, Vol. XX(XX) 1–9

DOI: 10.47852/bonviewAAES32021844

BON VIEW PUBLISHING

An Overview of Infra-Red Image Processing Based Oral Cancer Detection Technique

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Abstract: Oral cancer is often detected late, requiring timely and precise identification to enhance patient results and cut medical expenses. This study delves into the effectiveness of Infrared Imaging (IR) in spotting cancer, highlighting its ability to record temperature changes linked to abnormal developments. The study highlights the need for precise diagnostic equipment to address demanding situations when acquiring infrared images from the oral cavity. This system uses thermal imaging to extract and analyze the temperature-based statistical information for predictions. With promising outcomes from a rigorous evaluation of 24 subjects, the device demonstrates a sensitivity of 66.67% and specificity of 66.67%, indicating room for development. The study has looked at the significance of collaborative research and a set of regulations refinement, using SVM classifiers and Fuzzy logic for proper judgment to enhance the system's diagnostic accuracy and effect on healthcare results. The findings emphasize the essential position of IR generation in revolutionizing oral cancer screening structures, highlighting the need for continued research and collaboration to optimize its software.

Keywords: infrared imaging, image processing, feature extraction, machine learning, oral cancer diagnosis

1. Introduction

Oral cancer is generally detected at a late stage with a high mortality rate and leads to increased healthcare costs. So, early detection is crucial for this type of cancer in India. This article discusses cancer detection's importance, focusing on utilizing infrared (IR) imaging and image processing. In cancer research, the historical track of IR imaging can be traced back to the groundbreaking work covered in "Biomedical Engineering: Materials, Technology, and Applications" (Hossein Hosseinkhani, 2022). Recent research published in "Pharmaceutics"(Hosseinkhani et al., 2023) and (Domb et al., 2021) (Al-Fahoum et al., 2014)has further emphasized the potential applications of advanced imaging technologies in the field of cancer diagnosis and treatment.

While IR imaging has been associated with cancer research since 1961, recent technological advancements have reignited interest in its applications. IR imaging detects temperature changes in areas affected by cancer, where heightened metabolic activity creates hot spots. By utilizing temperature differences in tumour areas, where increased metabolic rates produce discrete "hot spots," IR imaging provides a non-invasive and promising option for detecting oral cancer in its early stages. However, the difficulties associated with collecting exact IR images from the complicated oral cavity, owing mainly to inherent camera focal length and size constraints, remain essential to overcome.

Conventional techniques for oral cancer diagnosis have notable limitations. These include a reliance on visual and manual examination, which can miss early-stage lesions, especially in hard-to-reach areas. Furthermore, tissue biopsy, a commonly used diagnostic method, is invasive and uncomfortable for patients, and it may only sometimes yield conclusive results. Other Radiological methods, such as X-rays and CT scans, give helpful information but expose patients to harmful ionizing radiation, which makes them less frequently used.

Researchers have recently investigated various methods, such as optical imaging, fluorescence, and genetic markers, to increase the accuracy and sensitivity of oral cancer screening. However, these approaches frequently struggle with expense, accessibility, and qualified personnel requirements. Additionally, while considerable progress has been achieved in early detection approaches, there is still potential for improvement.

The motivation of this effort is to address these constraints and difficulties. The team plans to employ infrared imaging (IR) technology to identify early signs of oral cancer by concentrating on its ability to identify temperature variations associated with pathological changes. This research also aims to develop a non-invasive, cost-effective, and reliable tool that could help in early diagnosis, improve patient survival rates, help in early assessment to improve patient survival rates and decrease the cost burden on healthcare providers. We aim to contribute to ongoing efforts to enhance oral cancer screening systems and, eventually, the level of patient care in this critical field of medicine by utilizing IR technology's advantages while resolving its limitations.

This study examines the enormous potential of infrared imaging for the early detection of oral cancer while being aware of the inherent advantages and disadvantages of the technology by highlighting the vital need for continued study and working with domain experts to optimize and develop oral cancer screening systems, assuring their applicability and efficacy in clinical settings where the findings contribute to the use of IR technology in healthcare.

2. Literature Review

Early diagnosis is essential to successfully manage oral cancer, improve treatment outcomes, and increase patient survival rates. Patients with oral cancer still experience high rates of morbidity and death, primarily as a result of late-stage detection and less effective therapy (Chakraborty et al., 2017; Wang and Wang, 2021). Although they have been used to identify oral cancer, traditional diagnostic techniques like X-ray and ultrasound imaging have inherent invasiveness and sensitivity limits. This study of the literature explores the development of medical imaging methods. It emphasizes how infrared imaging can be a promising, non-invasive, and compassionate way to detect oral cancer early on.

The use of ultrasound imaging has significantly improved the identification of oral cancer. Research like that of Richard Mammone et al. (2013) has focused on preprocessing methods to improve computer-aided detection in medical ultrasound images (Mammone et al., 2013). It has highlighted improvements in image quality achieved by methods like speckle reduction (Bhateja et al., 2014). Because oral tissues have acoustic qualities, ultrasound's ability to detect early mouth cancer lesions is still restricted despite its advantages in safety and accessibility.

Traditional X-ray imaging techniques have accomplished oral cancer screening, mostly in dental applications such as dental caries diagnosis (Zakian, Pretty, and Ellwood 2009). These techniques have limitations, though, and are less helpful in diagnosing oral cancer in general. Although X-ray imaging exposes patients to ionizing radiation and raises safety issues, ultrasound is less effective at penetrating tissue and providing detailed imaging within the deeper structures of the oral cavity.

In recent years, medical infrared thermography has become a viable non-invasive imaging method for identifying oral cancer. According to Cohen et al. (2013), infrared imaging uses the laws of thermodynamics to detect heat radiation from the body's surface, making it extremely sensitive to changes in temperature linked to oral cancer (Zhang et al., 2020). Studies such as those by Kapoor et al. (Kapoor and Prasad, 2010) and Hildebrandt et al. (Hildebrandt, Raschner, and Ammer, 2010) demonstrate the adaptability of infrared thermography in medical contexts. Simultaneously, Prof. Arie Orenstein's research (Prof. Arie Orenstein 2009) investigates the use of thermal imaging for oral cavity lesion identification. In 2018, Dong et al. researched the EGSVM-based infrared thermal imaging system. They investigated a low-cost, risk-free screening and diagnostic method for the identification of mouth cancer-related cervical lymph node metastases. While some researchers are creating automated processes for identifying oral cancer using infrared imaging, others are investigating the use of molecular imaging agents to improve the contrast between healthy and malignant tissues (Dixit, Kumar, and Srinivasan, 2023). According to Zhang et al. (2020), other researchers are looking into using the method of hyperspectral imaging, which takes pictures in many spectral bands, to increase the sensitivity and specificity of infrared imaging to detect oral cancer.

Infrared imaging has many benefits when it comes to detecting oral cancer. It is non-invasive, painless, and radiation-free, offering patients a safer alternative. Furthermore, even in the earliest phases of oral lesions, when structural alterations might not be apparent, it can detect temperature differences associated with them. Enhancing the precision and dependability of infrared imaging for diagnosing oral cancer is the primary goal of current research and development (Bhatnagar et al., 2018).

Other researchers are examining the ability of hyperspectral imaging, which takes snapshots in many spectral bands, to improve the sensitivity and specificity of infrared imaging for oral cancer diagnosis (Zhang et al., 2020).

Infrared imaging has numerous advantages in detecting oral tumours. It is non-invasive, painless, and radiation-free, which ensures patient safety. Furthermore, it may hit upon inflammatory abnormalities connected to oral diseases, even at their early stages, whereas structural changes may not be visible. Current studies and traits in infrared imaging for oral cancer detection are focused on improving the technique's accuracy and reliability (Bhatnagar et al., 2018).

Research efforts, including those of Chakraborty et al.(Chakraborty et al.,2016), investigated new methods to decorate the sensitivity and specificity of infrared imaging for oral cancer detection. Although ultrasound and X-ray imaging are helpful in clinical settings, their limitations in detecting oral lesions paved the way for the advent of infrared imaging. Infrared can detect inflammatory changes associated with cancerous growth before the naked eye even sees it (JARED SAGOFF, 2007). Infrared imaging holds great promise as a simple, non-invasive solution because of its ability to detect inflammatory changes associated with oral cancer. Future research must continue to refine the capabilities of this technology and potentially transform oral cancer they see in patient care.

3. Methodology

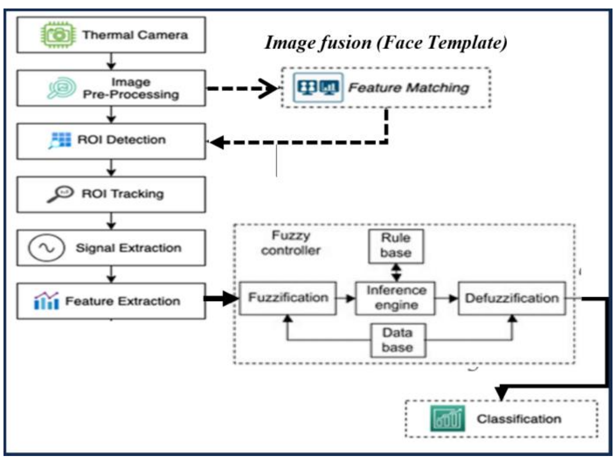
The methodological part of this observation outlines the particular workflow of a system developed for most oral cancer screenings that use infrared (IR) imaging. The following steps describe the device's purposeful improvements afterwards. Figure 1 illustrates the proposed framework, and Figure 2 provides the key factors of the framework development.

Figure 1
Illustration of the proposed system

3.1. Image acquisition

Infrared (IR) image capture is critical following the early identification of oral cancer. These photographs offer a unique perspective by collecting heat energy inside and outside the mouthpiece. Unlike visible light, infrared imaging may detect thermal changes associated with disease alterations, making it a useful diagnostic tool for oral cancer.

Figure 2
Main components for system development



3.2. IR image acquisition, processing and analysis

The infrared camera is essential for the Body Emission measurement software program. The system performs online image capture and preliminary image analysis simultaneously (after the image is captured electronically (i.e. in offline mode), the omitted statistics are extracted, and the data is transferred to Machine learning. Defined image processing and search algorithms are discussed below.

Images are captured using a thermal camera, the NI Vision Development Module, and the FLIR Thermo-Vision LabVIEW Toolkit. LabVIEW filters out impulse noise from each image.

3.3. Applying infrared imaging technology

The use of infrared technology in medical imaging is growing nowadays. Specific equipment like an Infrared camera and related software with a development kit is needed to fully utilize the potential of infrared imaging to detect oral cancer. The Thermo-Vision toolkit has been used here to collect infrared images, offering interpretation and analysis tools.

3.4. Diagnostic insights from IR images

The main goal of infrared imaging in oral cancer screening is to extract useful diagnostic data, which includes identifying anomalies and thermal irregularities in the acquired images.

It often shows areas of cancer, and these irregularities can appear as hot spots or abnormal temperatures. Feature extraction aims to describe these inflammatory changes, which can be used as markers to detect oral cancer early.

For oral cancer diagnosis, the acquisition and analysis of IR images help to identify thermal images that may indicate malignancy. The technology uses thermo-vision tools to understand better this thermal signature and potentially important insights into biomedical imaging.

3.5. Workflow of the system

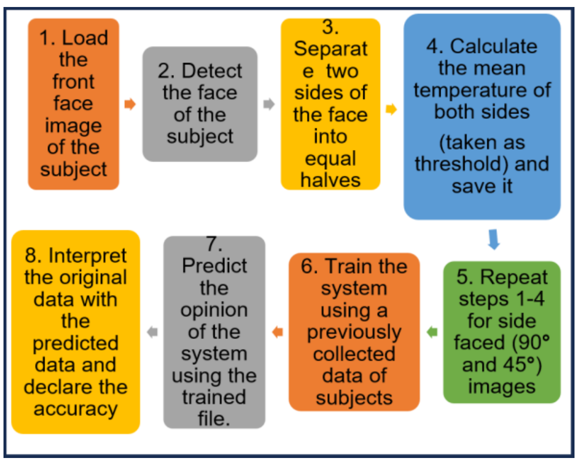
The workflow of the system is discussed in Figure 3.

1) **Load the subject's front-face image**: The subject's front-facing image is loaded, which is a preliminary input for further processing.
2) **Detect the face of the subject**: It is crucial to detect the subject's face from weighted images. This guarantees that future thermal analysis concentrates only on the frontal area.
3) **Separate two sides of the face into equal halves**: The next step is to separate the two sides of the face into two equal parts. This facilitates comparing temperature changes between the left and right sides of the face.
4) **Calculate the mean temperature of both sides (threshold) and save it**: The mean temperature on each side of the face is calculated using the developed image analysis tool. This intermediate temperature represents the initial temperature of each side of the face and is used as a threshold for further analysis.
5) **Repeat steps 1-4 for side-faced (90° and 45°) images**: The procedures described above are repeated for Images captured at different angles, particularly 90° and 45° angles. This multidimensional method improves the system's ability to detect temperature abnormalities from multiple angles.
6) **Train the system using previously collected data of subjects**: The algorithm is developed and trained to detect temperature patterns associated with oral cancer. This phase uses previously gathered participant data, allowing the system to learn and identify probable cancer-related temperature fluctuations.

7) **Predict the opinion of the system using the trained model**: After successful training, the system generates predictions using newly obtained IR images. It examines temperature patterns and makes diagnostic recommendations, noting whether the image data indicates the presence of oral cancer.

8) **Interpret the original data with the predicted data and declare the accuracy**: In the final step, the system compares its predictions to the original data. It tests the accuracy of its diagnosis by comparing its predictions to the known outcomes of the subjects in the dataset. This phase guarantees the reliability and efficacy of the developed oral cancer screening system.

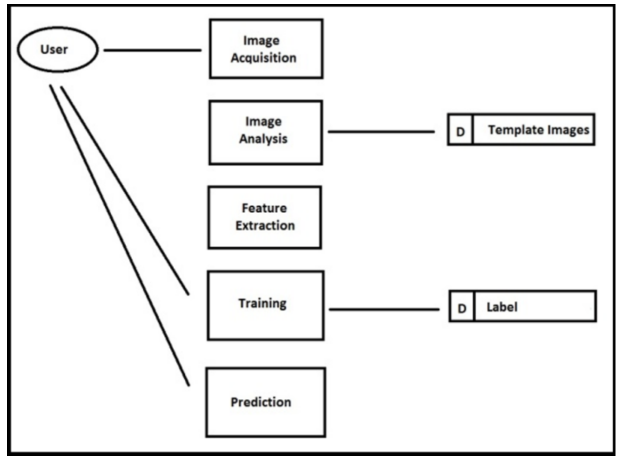
Figure 3
Workflow of the entire system



3.6. Data flow diagram (DFD) of the system (level 1)

Figure 4 shows the high-level data flow diagram (DFD) through the system. It describes user interactions, image acquisition, training, prediction, and various processes in generating IR images, including template image generation and feature extraction. This diagram provides insight detailing data paths and changes to the system.

Figure 4
DFD (Level-1) of the system



3.7. Features extracted from IR image analysis

3.7.1. Image processing features

In computer vision and image processing, features denote valuable information for addressing specific computational tasks, much like those used in machine learning and pattern recognition (Chucherd, 2014). These features can encompass various aspects, from specific structures within the image, like points, edges, or objects, to properties of regions within the image. The selection of features depends on the problem, and two approaches are commonly used in feature extraction: one that makes local binary decisions about feature presence at specific image points and another that produces non-binary data. The outcome of feature detection can be represented as sets of connected or unconnected coordinates of image points where features were detected, often with sub-pixel precision(Chen & Lee, 2014).

3.7.2. Feature detection

Feature detection in laptops is imaginative and prescient, and picture processing involves analyzing particular attributes at every point in an image to become aware of excellent capabilities that may show up as isolated points, non-stop curves, or linked regions [(Mammone et al., 2013)]. The definition of a function can range based on the hassle or utility but generally relates to an "interesting" thing of an image. The characteristic detector significantly affects the effectiveness of the set of rules, requiring repeatability in detecting equal characteristics across multiple images. Pixel evaluation performs an essential function in, with a bit of luck, identifying functions within a photograph regularly in the feature's vicinity. Additionally, using a Gaussian kernel in scale-area representation allows the technique of the input picture quickly, contributing to the calculation of function images via nearby image spinoff operations. Advanced algorithms can prioritize specific image areas for green feature detection, with various detectors available to cope with one-of-a-kind functions, computational complexities, and repeatability concerns.

3.7.3. Feature extraction

Localized image patches related to the characteristic set are extracted following characteristic detection, frequently requiring considerable image processing (Anon n.D.) (Chakraborty et al., 2016). These attributes are then analyzed and combined to create a characteristic descriptor or vector. The feature detection step can also offer supplementary attributes like side orientation and gradient significance in aspect detection or polarity and energy of the blob in blob detection (Bhateja et al., 2014). Feature description methods additionally consist of N-jets and neighbourhood histograms, with examples like the scale-invariant feature remodelling the usage of local histograms. Feature extraction without local resolution results in the identified image containing the same spatial or temporal variations as the original image, which contains image-featured data instead of intensity or colour information. Feature images are often computed as part of the feature recognition process. These images are the result of a combination of steps in the algorithm.

4. Software Interface at Different Developmental Stages

In this section, we provide a detailed discussion of the imaging models used in our study, which is our approach to oral cancer screening using infrared (IR) imaging and image processing techniques.

Figure 5
Thermogram of a subject, two parts of the face after thresholding

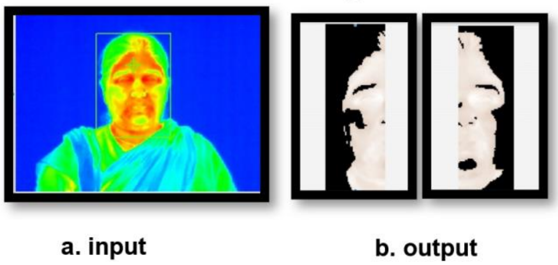


Figure 5a shows the thermogram acting as the first input to our system. This figure was captured from a subject's oral cavity and taken from the subject's face. It forms the basis of our analytical and testing methods, allowing us to detect temperature changes that may indicate possible distortion. Figure 5b shows the results of our image processing pipeline after applying thresholding techniques. An illustration of the title cover is divided into two parts.

Figure 6
The final output of the algorithm for extracting features from the front-faced image

Figure 6 presents the ultimate output of our feature extraction algorithm applied to the front-faced image. It encapsulates the features and temperature patterns our system identifies as potentially relevant for oral cancer screening. These features help to form the basis for subsequent analysis and predictions.

Figure 7
Thermograms of the Subject from 45° and 90° Angles

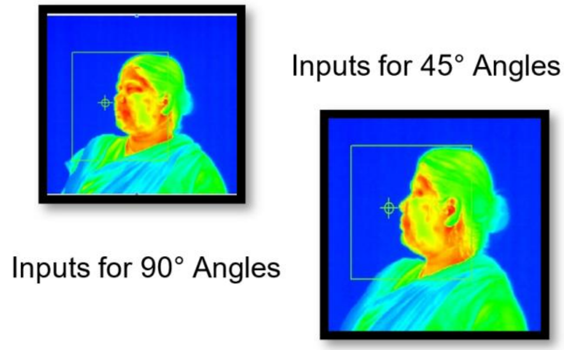


Figure 7 depicts IR images of the subject's oral cavity from alternative angles (45° and 90°). These images offer diverse perspectives for the analysis and broaden our system's capability to detect temperature irregularities from various orientations.

Figure 8
The output of the training algorithm

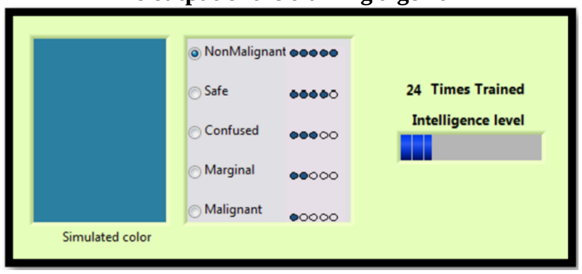


Figure 8 showcases the results of our training algorithm, which employs fuzzy logic to extract non-malignant, malignant, marginal, safe, and confused information based on the intelligence level. This information is instrumental in training our system to recognize patterns associated with oral cancer.

Figure 9
The output of the prediction algorithm

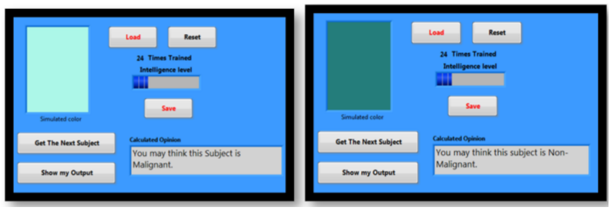


Figure 9 represents the output of our prediction algorithm, which utilizes the knowledge gained from the training phase to assess new data. It provides diagnostic opinions, indicating whether the acquired IR image data suggests the presence of oral cancer.

Figure 10
Block diagram for front face feature extraction

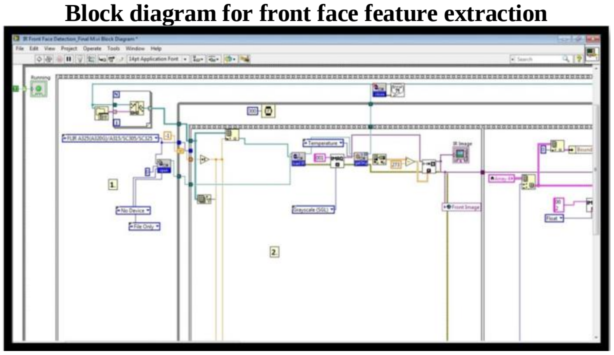


Figure 10 provides a Block Diagram that illuminates our software's internal operations. This diagram shows the sequential procedures involved in front-face feature extraction, file loading and Kelvin to Celsius temperature conversion. It explains the fundamental reasoning behind the feature extraction procedure, guaranteeing exact and correct outcomes. These front panel screenshots and VI block diagrams comprise the user interface and underlying algorithms of virtual instrumentation-based oral cancer screening software. They represent the intuitive user interface that allows people to engage with our system and the complex procedures in charge of feature extraction, training, and prediction—all essential components in our quest for early oral cancer diagnosis.

5. Challenges in Oral Image Capturing

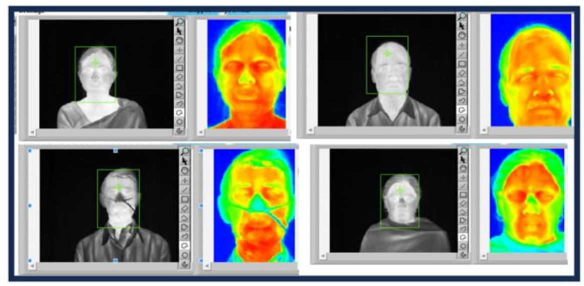
There are limitations to the IR camera in the mouth to the palate. Developing any comprehensive system of evidence for the extent of nasal hyperplasia is difficult. A standard IR camera has a lens size of 143×195×95mm (4.2×7.9×4.9) inch and a length of 24.6mm (25°). The camera lens size is much larger than the buckle cavity. It does not penetrate the mouth properly.

However, the problem area is usually in the hidden parts of the face, which are critical for imaging. The focal point and maximum focal length of the IR image prevent the imaging system from capturing a sufficiently close image of the subject; It will be off-centre. Thus, the infra-red imaging was mainly focused on the oral cavity and its attachment area(Boussada et al., 2014; Diakides & Bronzino, 2007; Hartmut Surmann & lexander Selenschtschikow, 2002).

5.1. Samples of some oral cancer subjects

Figure 11 shows some images of the subjects for facial expression data collection in oral cancer screening.

Figure 11
Sample images of the subjects for the front-face data collection on oral cancer analysis



IR images are captured from five angles: front, 45 degrees Right and Left, and 90 degrees left and right. However, all the images are taken from outside the face. If any complexities occur on the outer side of the face, this system is ideal. On the other hand, if the complexities are found in the inner cavity, the effect has not reached the surface of the outer face. In that case, this system will not work.

6. Results and Discussions

The current system utilizes thermal imaging with an infrared (IR) camera according to a defined method for image acquisition and subsequent analysis. The core of this procedure is gathering mean temperature readings from various facial regions, which are segregated according to preset threshold criteria. The system's training is based on this extracted feature, which functions well as a thermal signature. The training prepares the algorithm to make predictions when presented with new data, allowing for the early detection of oral cancer. To rigorously examine the system's functionality and reliability, we conducted experiments on 24 participants. Each side of a subject's face was treated separately, totalling 24 cases, using a population-based case-control study design. This approach enables us to examine the system's effectiveness across various conditions. This approach allowed us to comprehensively assess the system's effectiveness across diverse circumstances.

The outcome of these evaluations is presented in Table 1, providing a multifaceted understanding of the system's efficiency.

Table 1
Population-based case-control study

Population-based case-control study	Subject numbers
Total positive	4
Total Negative	12
False Positive	6
False Negative	2
Sensitivity	66.67%

Specificity	66.67%
Positive Predictive Value	40%
Negative Predictive Value	85.71%
Accuracy	66.66%
False Negative ratio	33.33%
False positive ratio	33.33%
LR+	+2
LR-	0.5
Diagnostic Odd Ratio	4

The equations aforementioned denote the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

The automated approach shows excellent potential for smooth diagnostic system integration. To ensure its dependability and ethical approval, it underwent lengthy training on a meticulously generated dataset from Cachar Cancer Hospital in Silchar (CCHRC/IRB/01/2019/254).

The developed virtual instrumentation module using LabVIEW completes the solution, providing a clinically usable platform for efficient oral cancer screening using infrared imaging.

One of the future goals of the research is to implement Support Vector Machine (SVM) classifiers in LabVIEW for improved analysis and comparison of Genfis-based and SVM-based processes.

All sensitivity, specificity, and predictive values should be considered when evaluating overall system performance. The system has a sensitivity of 66.67%, which means it can detect those at risk of developing oral cancer. However, new ones are needed to prevent false negatives and increase sensitivity.

A specificity of 66.67% is necessary for the correct classification of healthy individuals, but additional variability may increase confidence in pessimistic predictions. A positive predictive value (PPV) of 40% indicates caution in interpreting optimistic predictions and emphasizes the importance of confirmatory testing.

The high negative predictive value (NPV) of 85.71% reduces the risk of missing truly negative data, which is reassuring. The overall system accuracy is 66.66%, which reveals room for algorithm improvement. Any balanced false-negative and false-positive ratio of 33.33% is challenging and requires an optimal trade-off between sensitivity and specificity.

Positive predictivity (LR+) of +2 indicates promise in established risk profiles, while a negative (LR-) of 0.5 reduces the likelihood of false positive and negative results. The diagnostic odds ratio of 4 indicates diagnostic performance is considered, but continued effort is required to improve further.

The chart demonstrates the early detection of oral cancer using IR imaging and imaging techniques. Collaborative analysis and algorithms incorporating SVM classifiers are needed to improve sensitivity, specificity, and accuracy.

When evaluating the performance of our system, it is essential to compare it with existing methods and compare them with the context. Although this review mainly focuses on IR imaging for oral cancer detection, we acknowledge the existence of traditional diagnostic methods such as ultrasound and X-ray imaging.

Also, these traditional techniques are valuable but have limitations when detecting nasal lesions, especially in the early stages. The emergence of IR imaging as a terrific, touching, and promising answer is highlighted in this paper. This generation effectively takes advantage of the thermal changes associated with cancer sites, making it particularly suitable for most oral cancers. "Unlike traditional strategies, this approach offers the benefit of the usage of non-ionizing radiation, which guarantees patient safety".

In the case of IR imaging, challenges arise from the limitations of camera size, especially within the oral cavity. However, these challenges are outweighed by the potential benefits of early detection and non-invasiveness, which can significantly impact patient outcomes and healthcare costs.

7. Conclusion

This work extensively examines the capability of infrared (IR) imaging and photograph processing in early oral cancer prognosis. Acknowledging the essential role of set-off prognosis in improving affected person results, we examine the drawbacks of traditional diagnostic strategies and X-ray and ultrasound imaging in detecting oral lesions.

Infrared imaging has emerged as a touchy, non-invasive, and promising approach. This device is handy for diagnosing most oral cancers since it uses temperature variations connected to malignant tissues. Although its advantages were cited, we also mentioned the problems in taking infrared pictures in the mouth because of digital camera length restrictions.

They have a radical approach to illustrating the organized process of creating oral cancer screening.

The paper offers a detailed methodology illustrating the systematic workflow of the developed oral cancer screening system. It encompasses essential steps from picture acquisition to characteristic extraction, emphasizing the importance of multi-angle image evaluation and machine schooling using considerable datasets.

Encouraging data came from an evaluation of program performance involving 24 individuals. The system's sensitivity, specificity, and predictive values demonstrate its effectiveness in comprehensively analyzing the relevant data. Its reliability is demonstrated by its inclusion in research design and training with intensive data collection from Cachar Cancer Hospital.

The policy we have described in this review has essential and broad implications. The observation highlights the cost of early detection of most oral cancers by highlighting the potential of infrared (IR) imaging to overcome the shortcomings of traditional diagnostic strategies. Facilitating early intervention increases test accuracy and improves patient effects by moving to noninvasive and handy technologies.

In addition, virtual instrumentation through LabVIEW presents a versatile basis for classy scientific diagnostic structures using infrared imaging. Subsequent coursework will focus on integrating new techniques, including Support Vector Machine (SVM) classifiers in LabVIEW, to facilitate more significant complex evaluation and prediction. In addition, the device's overall performance can be progressed with the aid of comparative evaluation among Genfis-based techniques and SVM classifiers to enhance early and specific oral cancer detection.

Acknowledgement

The technical contributions of Smt Sayantani Banerjee, Sri Tarun Karak, and the technical coordination of Smt Barnali Pal are sincerely acknowledged. Also, Dr. R. Ravi Kannan and his team are acknowledged for providing hospital support for data collection and test beds. In addition, Sri Aditya Kumar Sinha, Center Head, C-DAC, Kolkata, has provided constant support and help with the implementation. MeitY (Ministry of Electronics and Information Technology), Govt. of India, funded this project, bearing administrative approval No. 1(4)/2015- ME&HI.

Ethical Statement

The study was approved by the Cachar Cancer Hospital and Research Centre IRB/Ethics Committee bearing approval number CCHRC/IRB/01/2019/254.

Conflicts of Interest

The authors declare that they have no conflicts of interest in this work.

Data Availability Statement

Data sharing does not apply to this article as no new data were created or analyzed in this study.

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How to Cite: Bandyopadhyay, A., Sekhar Mondal, H., Dam, B., & Chandra Patranabis, D. (2023). An Overview of Infra-Red Image Processing Based Oral Cancer Detection Technique. Archives of Advanced Engineering Science. https://doi.org/10.47852/bonviewAAES32021844