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AI powered model for Oral-cancer Detection

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Abstract—Oral cancer detection, a critical health challenge due to late-stage diagnoses, has seen significant advancements through the integration of both hardware and software technologies. The system, designed for the early detection of oral cancer, combines innovative hardware, such as robotic arms for assistive feeding, cost-effective control systems for industrial robotics using Raspberry Pi, and Io T-enabled devices for remote oral examinations, with advanced software solutions. These hardware systems utilize lightweight structures, motorized joints, stepper motors and precise motion control to enhance functionality in healthcare and industrial environments. For early detection, Machine Learning (ML) and Deep Learning (DL) techniques, including Convolutional Neural Networks (CNNs) and transfer learning models like VGG19 and InceptionNetV3, Res-Net and Dense-Net, have been employed to analyze medical images. Image processing methods such as GLCM, wavelet transforms, and CNN-based feature extraction improve classification accuracy, while optimization techniques like Fuzzy Particle Swarm Optimization (FPSO) and Artificial Bee Colony (ABC) enhance performance. The integration of these systems achieves high sensitivity, specificity, and precision, making them effective in early oral cancer detection. By combining advanced diagnostic technologies, the system offers a comprehensive approach that improves early diagnosis, enhances patient outcomes, and complements traditional methods.

Key Words: Oral Cancer, machine learning, early detection.

1. INTRODUCTION

Oral cancer, particularly Oral Squamous Cell Carcinoma (OSCC), remains one of the leading causes of cancer-related morbidity and mortality worldwide. The high mortality rate associated with oral cancer is largely due to late-stage detection, which reduces the chances of successful treatment. In particular, individuals with Oral Potentially Malignant Disorders (OPMD's) face a significantly higher risk of developing OSCC. Early detection of these conditions is crucial to improving survival rates, as it allows for timely intervention and more effective treatment. However, traditional diagnostic methods often rely on clinical visual examinations and biopsy procedures, which are not always efficient, timely, or accessible, especially in low-resource settings. Therefore, there is a critical need for more efficient, accurate, and accessible methods of detecting oral cancer in its early stages.

To address this issue, we propose a novel approach that combines the power of modern hardware systems with advanced software technologies for the early detection of oral cancer. The system integrates several cutting-edge technologies, including robotic arms, Io T devices, and machine learning (ML) algorithms, to offer a comprehensive solution that not only detects oral cancer but also facilitates remote diagnostic procedures and enhances the accessibility of care.

The hardware component of this system includes robotic arms designed for assistive purposes, such as feeding elderly or specially challenged individuals, and Io T-enabled devices that enable dentists to perform preliminary oral examinations from a safe distance. These systems use lightweight structures, motorized joints, and precise control mechanisms, which improve the ease of operation and adaptability in healthcare environments. For industrial applications, cost-effective control systems using Raspberry Pi and IP cameras are employed to control robotic arms, showcasing the versatility of the platform.

The software aspect of the system relies on machine learning and deep learning techniques, such as Convolutional Neural Networks (CNNs), to analyze oral histopathology images for early signs of oral cancer. These algorithms are trained using large datasets of annotated medical images and employ advanced image processing methods, including Gray Level Co-occurrence Matrix (GLCM), wavelet transforms, and CNN-based feature extraction, to identify malignant lesions with high accuracy. Optimization techniques like Fuzzy Particle Swarm Optimization (FPSO) and Artificial Bee Colony (ABC) are used to improve model performance and accuracy. The integration of these advanced technologies into a single platform enables early detection of oral cancer, which can significantly improve diagnostic efficiency and patient outcomes.

The primary aim of this project is to develop a robust and reliable system that facilitates the early detection of oral cancer in a cost-effective way through a combination of innovative hardware and software. By integrating automation, Io T, and artificial intelligence, the system has the potential to revolutionize oral cancer diagnostics, making it more accessible, efficient, and effective. This approach not only addresses the challenges faced by traditional diagnostic methods but also paves the way for more personalized and precise treatment strategies in the fight against oral cancer. The following sections of this paper will discuss the design and development of the hardware components, the software algorithms employed for oral cancer detection, and the integration of these technologies to create a cohesive system for improving diagnostic accuracy and patient care.

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2. Literature review

A. *Software Implementation Analysis:*

Machine Learning for Early Detection of Oral Cancer: Oral squamous cell carcinoma (OSCC) is a life-threatening cancer often diagnosed late, with Oral Potentially Malignant Disorders (OPMDs) increasing its risk. This study utilized machine learning (ML) to analyze 360 clinical intraoral images for detecting OSCC and OPMDs.Images were annotated by expert pathologists and processed using Roboflow software for multiclass object detection. The ML model achieved a mean average precision (mAP) of 25.4%, precision of 29.8%, recall of 32.9%, sensitivity of 88.9%, and specificity of 75%, with a kappa statistic of 0.7, indicating moderate agreement with clinicians. The results highlight the potential of ML as a supportive tool for early detection of oral lesions, improving diagnostic efficiency and patient outcomes. While performance requires enhancement, this approach shows promise for complementing traditional methods in cancer diagnosis [1].

Artificial Intelligence and Machine Learning in Oral Cancer Detection: The paper delves into the evolving role of Artificial Intelligence (AI) and Machine Learning (ML) in the early detection and management of oral cancer, a pressing global health issue. It highlights key advancements in AI-driven technologies, such as Convolutional Neural Networks (CNNs) and Computer-Aided Detection Systems (CAD), emphasizing their ability to enhance diagnostic accuracy through image analysis, pattern recognition, and predictive modeling. The study also explores the integration of smartphone-based probes and Optical Coherence Tomography (OCT), demonstrating their potential to improve accessibility and real-time diagnostics. Despite these technological strides, the paper identifies challenges like data limitations, ethical considerations, and the need for specialized training as barriers to broader implementation.

The authors advocate for interdisciplinary collaboration among healthcare professionals, data scientists, and policymakers to overcome these challenges, paving the way for AI to revolutionize oral cancer screening. The review underscores the importance of rigorous research, ethical safeguards, and the integration of AI into clinical workflows, ultimately aiming to improve patient outcomes through precision and accessibility in diagnostics [2].

Deep Learning for Oral Cancer Diagnosis and Management: Current Trends and Future Directions.The paper explores the transformative potential of deep learning (DL) in diagnosing and managing oral cancer, a critical global health issue with high mortality rates due to late-stage detection and limited healthcare access. It highlights the application of various DL techniques such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) in diagnosing oral cancer from medical imaging, predicting disease progression, and personalizing treatment strategies. The paper emphasizes the importance of oral cancer databases for advancing research and clinical practice and discusses challenges like data variability and model interpretability. It calls for further research and collaboration to optimize DL methods for oral cancer treatment, ultimately improving early detection, precision medicine, and patient outcomes [3].

Oral Cancer Detection using Machine Learning and Deep Learning Techniques- The paper “Oral Cancer Detection using Machine Learning and Deep Learning Techniques” focuses on the development of an automated system for the early detection of oral cancer, a critical health issue due to its high mortality rate. The study aims to build a robust dataset of annotated oral lesions and uses both machine learning (ML) and deep learning (DL) techniques for classification. The authors employed traditional ML models, such as Naïve Bayes, KNN, SVM, and ANN, along with a custom Convolutional Neural Network (CNN) model, to classify oral lesions as malignant or benign. The CNN model, in particular, demonstrated superior performance, leveraging a 43-layer deep architecture inspired by the VGG-16 network. The methodology includes image segmentation for lesion detection, feature extraction using techniques like GLCM, Gabor features, and color analysis, followed by classification using the mentioned algorithms. A dataset of 1200 images (600 malignant and 600 normal) was used for training, with image augmentation applied to enhance the dataset for deep learning purposes. The performance of these models is thoroughly analyzed, showing that deep learning, especially CNN, offers high accuracy in detecting oral cancerous lesions. The paper concludes that the proposed models, particularly the deep learning CNN model, offer an efficient solution for the automated classification of oral cancer lesions, which could lead to early diagnosis and improve treatment outcomes [4].

Oral Cancer Detection Using CNN: This paper discusses the use of Convolutional Neural Networks (CNN) for the automated detection of oral cancer through image processing techniques. Oral cancer is a major health issue, especially prevalent in low- and middle-income countries, with high mortality rates due to late-stage diagnosis. The paper explores how early detection of oral cancer can be achieved through the identification of potentially malignant lesions during routine clinical oral examinations (COE). The proposed method involves image processing to detect oral lesions, starting with acquiring input images, followed by preprocessing (enhancing image quality, removing distortions), resizing, filtering, and segmentation. The CNN algorithm is used to classify the images into categories based on the features identified through several layers, including image input, batch normalization, pooling, and fully connected layers, with the final softmax and classification layers providing the output. This system aims to improve the efficiency of oral cancer detection while making the process more cost-effective and accessible, especially in areas with limited resources. The results demonstrate that the proposed CNN-based approach is effective in distinguishing between different parts of oral images, such as background and bone, which helps in the diagnosis of oral cancer. The method is user-friendly, requires minimal hardware, and is more efficient compared to existing techniques [5].

Improving Oral Cancer Detection Using Pretrained Model- The study begins by acknowledging the limitations of traditional diagnostic methods in identifying oral cancer, which can lead to late-stage diagnoses and poorer patient prognoses. To address this issue, the authors implement a series of experiments using these DenseNet models, which are pretrained on large-scale image datasets. This allows the models to leverage learned features, improving their ability to distinguish between malignant and benign lesions in oral tissue images.The authors detail their methodology, including data preparation, model training, and validation processes. They conduct experiments comparing the performance of different DenseNet models, evaluating metrics such as accuracy, precision, recall, and F1-score. Results indicate that the pretrained models significantly outperform conventional imaging techniques, achieving higher accuracy rates in both classification tasks and detection scenarios.The research emphasizes the practical implications of this technology, envisioning its integration into clinical workflows. By providing healthcare professionals with tools that enhance the early detection of oral cancer, the study contributes to the growing field of computational pathology and highlights the potential of machine learning in transforming cancer diagnostics.Overall, the findings underscore the importance of utilizing advanced AI techniques in healthcare and encourage further exploration of machine learning applications in various diagnostic medical fields [6].

Oral Cancer Diagnosis using Deep Learning for Early Detection: The core idea behind the paper is to use CNNs, a powerful deep learning method well-suited for image analysis, to classify oral tissue images as cancerous or non-cancerous. CNNs can automatically learn hierarchical features from images, which makes them highly effective for complex pattern recognition tasks like medical image classification. However, the performance of CNNs largely depends on the appropriate selection of hyperparameters, such as the learning rate, the number of layers, and the size of the convolutional filters. In this study, the authors integrate FPSO to optimize these hyperparameters, aiming to improve the accuracy, sensitivity, and specificity of the CNN model.FPSO is a hybrid optimization algorithm that combines Particle Swarm Optimization (PSO), which is a global optimization technique inspired by the social behavior of birds flocking, with fuzzy logic. The fuzzy component in FPSO helps handle uncertainties or imprecision in the model's parameters, making it well-suited for tasks where the data may not be perfectly clean or where there are ambiguities in the classification process. The authors use FPSO to fine-tune the CNN, ensuring it learns the best possible set of features for detecting oral cancer in images. The optimized CNN model is then trained on a dataset of labeled oral tissue images, which has been classified as benign or malignant. The results from this approach show that the CNN model, when optimized with FPSO, significantly outperforms traditional machine learning classifiers in terms of diagnostic performance. The FPSO-optimized CNN achieved higher accuracy, sensitivity, and specificity in classifying oral cancer images compared to other models. The system was able to automatically identify malignant tissues with high precision, demonstrating the effectiveness of combining deep learning and optimization techniques for cancer detection. By automating the classification process, the system reduces human error, enhances consistency, and speeds up the diagnostic workflow, which could be especially valuable in busy clinical settings[7].

Oral Cancer Diagnosis using Deep Learning for Early Detection. This study explores the use of pre-trained deep learning Convolutional Neural Networks (CNN) models, namely VGG19, InceptionNetV3, and Xception, for the automated detection of oral cancer. The models are utilized with transfer learning to leverage knowledge from large datasets and adapt them for oral cancer detection tasks . Oral Cancer Detection Using Deep Learning Approach - This paper presents a deep learning-based approach to oral cancer detection. It incorporates advanced techniques like Fuzzy Particle Swarm Optimization (FPSO) for feature selection and Artificial Bee Colony (ABC) for optimization. The Convolutional Neural Networks (CNN) are used for the classification task. The study explores how these optimization algorithms can improve CNN performance, particularly in terms of precision and recall for detecting oral cancer in medical imaging [8].

Early Cancer Detection using Deep Learning and Medical Imaging: A Survey - This survey paper reviews various deep learning techniques and medical imaging methods used in early cancer detection. The paper provides a comprehensive analysis of feature extraction methods, including Histogram of Oriented Gradients (HOG), Gray Level Co-occurrence Matrix (GLCM), wavelet transforms, and advanced deep learning models like CNN, RCNN, YOLO, Vision Transformer, and GANs. Oral Cancer Detection Using Convolutional Neural Network Optimized by Combined Seagull Optimization Algorithm. This research investigates the use of a Convolutional Neural Network (CNN) optimized with a combination of Seagull Optimization and Particle Swarm Optimization algorithms for oral cancer detection. The study focuses on enhancing CNN's performance in medical image classification tasks. The paper shows that the hybrid optimization technique improves accuracy by effectively tuning the hyperparameters of the CNN, thus making it more efficient in detecting oral cancer from images [9].

Performance Analysis of Convolutional Neural Network (CNN) Based Cancerous Skin Lesion Detection System - This paper evaluates the performance of CNN in detecting cancerous skin lesions. The authors propose the Batch Normalized Convolutional Neural Network (BN-CNN) to improve the CNN’s performance by stabilizing the learning process. The paper highlights the importance of batch normalization in enhancing the accuracy of skin lesion detection, which is crucial for early-stage skin cancer [10].

Diagnosis of Oral Squamous Cell Carcinoma Using Deep Neural Networks and Binary Particle Swarm Optimization on Histopathological Images: An AIoMT Approach - This paper presents an AIoMT (Artificial Intelligence of Medical Things) approach for diagnosing Oral Squamous Cell Carcinoma (OSCC) using deep neural networks (DNN) and binary particle swarm optimization (BPSO). The authors use histopathological images to train deep learning models like VGG16, AlexNet, ResNet50, and Inception V3 to detect OSCC. The binary particle swarm optimization technique is employed to fine-tune the models for better classification performance. The study demonstrates the efficacy of these deep learning mode [11].

B. Hardware Implementation Analysis:

Intelligent Image Base Visual Serving controller for Robot Arm: The paper discusses an intelligent image-based visual serving (IBVS) controller for robotic arms using reinforcement learning (RL). It leverages Q-learning to determine control gains, enabling precise arm movements based on visual feedback. The proposed system uses feature error distances between current and target images to define state space and employs a reward mechanism to refine control policies over multiple iterations. Simulations using a 7-axis robotic arm demonstrate the approach's efficiency, showing reduced serving time and improved trajectory stability compared to fixed control gains. The method simplifies controller design while maintaining effectiveness in dynamic environments[12].

Automation of end effector guidance of robotic arm for Dental Implantation using Computer Vision: The paper presents a robotic arm system for dental implantation, automating the precise task of drilling in a human jaw using computer vision. A cylindrical robotic arm, equipped with a drill and an endoscopic camera, uses template matching for accurate guidance to the drill site. The proposed method employs a closed-loop feedback system for continuous adjustments based on live video feed, ensuring precise alignment even with patient movement. The control system, driven by a Raspberry Pi and Arduino, achieves sub-millimeter precision. Tested successfully, the system reduces dentist effort while improving surgical accuracy, paving the wayfor further healthcare [13].

The design, construction, and application of robotic arms in industrial and other settings. It explores components like actuators, sensors, controllers, and power sources, emphasizing robotic arms' adaptability and precision in tasks like welding, material handling, and hazardous environments. The study highlights kinematics, focusing on forward and inverse kinematics for precise movement. A prototype using an Arduino Nano, servomotors, and Bluetooth connectivity for remote control is presented, with applications in military, rescue, and industrial automation. The robotic arm improves efficiency, reduces labor costs, and performs tasks in challenging environments, showcasing advancements in robotics for multipurpose use [14].

The design and construction of an Arduino-based robotic arm controlled via a mobile application over Bluetooth. The robotic arm, with six degrees of freedom, includes five rotary joints and a gripper. Components are 3D-printed and assembled, featuring MG945 and MG90S servo motors for motion. The Arduino platform processes commands sent from the mobile app sliders, adjusting motor movements accordingly. The prototype was tested for speed, force, and precision, demonstrating effective handling of weight and stability. Applications range from industrial automation to hazardous environments, where human safety is paramount. The system's modularity, low cost, and remote-control capabilities underline its potential for widespread industrial and educational use, advancing robotic technologies in versatile environment [15].

Real time Image Processing based Robotic Arm Control Standalone System using Raspberry pi:The paper explores a real-time image processing robotic arm system using Raspberry Pi for object detection and control. By leveraging OpenCV and MATLAB, the system detects and follows objects, specifically green ones, using Raspberry Pi running on Raspbian OS. The hardware includes a robotic arm with servo motors, a camera, relays, and a power supply. The Raspberry Pi processes images, converts them to grayscale, identifies the target object, and directs the arm for operations such as pick-and-place. Experiments demonstrated precise detection, tracking, and motion control, with improvements over earlier systems in efficiency and accuracy. This cost-effective and versatile solution is suited for industrial automation and surveillance applications, showcasing advancements in robotic arm control [16].

Design and Development of a Robotic Arm: This paper presents the design and development of a 5-DOF robotic arm tailored for assisting elderly or specially challenged individuals with feeding tasks. Built with lightweight aluminum, the arm integrates stepper and DC motors controlled via Arduino Mega2560, employing potentiometers and force sensors for precision. MATLAB algorithms verify kinematics through forward and inverse modeling, while a Graphical User Interface (GUI) facilitates intuitive control. The setup ensures accurate positioning and functionality. Testing confirms the system's reliability and adaptability, with potential for broader applications. This solution demonstrates advancements in robotic assistance, blending affordability and effectiveness for enhanced user interaction [17].

Industrial Robotic Automation with Raspberry PI using Image Processing: The development of an industrial robotic automation system powered by Raspberry Pi and SCORBOT-ER III robotic arm, with IP cameras for visual guidance. The system enables object sorting based on size, shape, and position through image processing. It highlights the potential of using low-cost, compact computing devices like Raspberry Pi for industrial automation. The proposed system adapts in real-time, offering precision and flexibility in dynamic environments. Future enhancements include migrating the system to FPGA or ASIC platforms for improved performance and integration [18].

Robotic arm with real-time image processing using raspberry pi, both automated and manually:The creation of a robotic arm that performs real-time image processing using a Raspberry Pi. The system can detect objects by color (RGB) and segregate them based on pre-defined characteristics. It operates in both automatic and manual modes, with the latter controlled via a local webpage interface. Python programming and image processing libraries are utilized for object detection and robotic arm control. The system is cost-effective, precise, and suited for industrial applications like sorting and segregating objects. Future enhancements focus on improving accuracy and operational flexibility, making it versatile for various tasks [19].

Development of an oral cancer detection system through deep learningThis study introduces a portable electronic oral endoscope integrated with deep learning to detect oral cancer early. Using a customized Zeiss lens and RGB imaging, it captures high-resolution intraoral images. U-Net and ResNet-34 models were utilized for segmentation and feature extraction. The dataset comprised 205 annotated images normalized for model training and validation. Metrics like Dice coefficient, IoU, precision, recall, and F1 score evaluated performance. Results highlighted precision up to 96% and recall of 100%. The system's limitations include dataset size and challenges in detecting early lesions. Future efforts aim to enhance its diagnostic accuracy and application scope [20].

Medical Image Classifications for 6G IoT-Enabled Smart Health Systems This paper focuses on developing a framework for medical image classification within a 6G-enabled Internet of Medical Things (IoMT) system. It employs deep learning for feature extraction using MobileNetV3 and enhances feature selection through a hybrid optimization algorithm combining Arithmetic Optimization Algorithm (AOA) and Hunger Games Search (HGS). The system demonstrates high performance in diagnosing diseases using datasets for skin cancer, blood cells, and retinal imaging. The integration of IoMT and 6G ensures rapid processing and scalability, while the framework outperforms existing models in accuracy, recall, and F1-score, marking a significant step in healthcare technology [21].

Teeth lesion detection using deep learning and the internet of things post-covid-19. This paper presents an IoT-based automated healthcare diagnosis model that uses deep learning, data augmentation, and transfer learning for teeth lesion detection. This system, developed in a post-COVID-19 context, reduces the need for in-person dental visits by using IoT-enabled devices to acquire periapical radiographs. These images undergo preprocessing, feature extraction using AlexNet (a convolutional neural network), and classification through SVM and KNN methods. Data augmentation addresses limited dataset issues, enhancing the model's accuracy to 98%. The research highlights the integration of IoT and AI in healthcare, offering potential applications in early detection and remote monitoring of dental health [22].

3. METHODOLOGY:

The methodologies implemented for this project in the research papers we have gone through involves an integrated approach that combines hardware for data acquisition, cloud-based deep learning for analysis, and a user-friendly interface for results delivery. The process encompasses image capturing using Raspberry Pi, cloud-based prediction using state-of-the-art deep learning models, and real-time communication between components via Flask API. SQLite is utilized for database management, while TensorFlow Lite enables lightweight model deployment for efficient predictions. The work flow is illustrated as follows:

1. Image capturing using Raspberry Pi.
2. Pre-processing and sending images to the cloud.
3. Cloud-based prediction using deep learning models (VGG-16, ResNet, DenseNet).
4. Results transmitted via Flask API to web application and storing results in Database using SQLite.
5.

A. *Hardware Setup:*

- Supply: The system is powered by an external power supply, which provides the necessary voltage and current to the Raspberry Pi and other components.
- 12V/5VBattery: A battery backup is provided, supplying either 12V or 5V. This ensures uninterrupted operation of the motor and other peripheral devices during power fluctuations.
- RaspberryPi5: The Raspberry Pi 5 acts as the main controller, processing inputs from the camera and executing the necessary commands for motor control. It manages data flow between components and outputs to the display.
- MotorDrive: This unit controls the stepper motor, which is used to drive mechanical movements. The motor drive receives control signals from the Raspberry Pi and converts them into precise motor actions.
- Stepper Motor: A stepper motor is employed for accurate and precise movement. This could be used to position or align the camera, or to perform specific mechanical operations.
- Camera: The camera captures images or video, which are processed by the Raspberry Pi. In this context, it could be used for monitoring or interacting with patients (e.g., detecting their condition, gestures, or tracking movements).
- Patients: The system is designed to interact with or monitor patients. This could involve capturing data through the camera for diagnostics, monitoring health conditions, or other applications.
- Display: The display outputs information processed by the Raspberry Pi. This could include visual data, results of monitoring, or user interface elements for caregivers or operators.

B. *Overview of Basic Components required:*

i. *Raspberry Pi 5:*
- Quad-core Cortex-A72 processor (1.5GHz).
- 4GB/8GB RAM.
- Built-in WiFi and Bluetooth for networking.
- HDMI and USB support for connecting peripherals.

ii. *Camera:*
- High-Resolution Intraoral Camera:
- Minimum 1080p (Full HD) resolution.
- Autofocus and LED lighting for detailed visualization.
- USB or compatible with Raspberry Pi camera interface.

iii. *Stepper Motor:*
- Torque: >0.5 Nm for smooth and precise movements.
- Step Angle: 1.8° or better for fine adjustments.
- Servo Motor (if required):
- Torque: ~2-5 kg.cm for additional movements.

iv. *Motor Drive:*
- Compatible with stepper motors (e.g., L298N or A4988 driver modules).
- Handles input voltage from 5-12V.

v. *Power Supply:*
- 12V/5V DC (battery or adapter): Ensures uninterrupted power to Raspberry Pi, motors, and camera.

vi. *Display:* Touchscreen LCD Display: 7-10 inches for real-time feedback and interaction.

vii. *Cloud Integration*:
- Deployment of Deep Learning Models:
- The preprocessed images are sent to the cloud for analysis.

- Flask API facilitate seamless communication between the Raspberry Pi and the cloud server.
- Models employed:
- VGG-16: Known for its simplicity and effectiveness in image classification.
- Res-Net: Used for its deep residual architecture to mitigate vanishing gradient problems.
- Dense-Net: Ensures feature reuse to improve efficiency and accuracy.

4. PREDICTION AND RESULT DELIVERY

Model Prediction:

- TensorFlow Lite is used to build and deploy lightweight versions of the deep learning models on the cloud for efficient inference.
- Predictions include the classification of oral lesions as malignant or benign.
- Result Communication:
- Flask API send the prediction results to a web application serving as the user interface (UI)

User Interface and Database Management

- **Web Application (UI):**
- A simple and intuitive web application presents results to healthcare professionals or users.
- Designed for accessibility and user-friendliness, ensuring smooth navigation.
- Database (SQLite):
- Stores patient information, captured images, and prediction results for future reference and analysis.

Communication Protocols Used

HTTP protocol for communication set-up between cloud, UI and the hardware.

5. HARDWARE METHODOLOGY

The proposed system integrates IoT and deep learning technologies to address the critical challenge of early oral cancer detection, and it has been compared to existing methods in terms of accuracy, scalability, cost-effectiveness, and ease of use. Traditional systems primarily rely on manual examinations or standalone diagnostic devices, which are often inaccessible in resource-limited settings. The reviewed literature highlights various approaches, including CNN-based image classification and Io T-enabled healthcare applications. However, many existing solutions lack real-time integration, user-friendly interfaces, or scalability for widespread deployment.

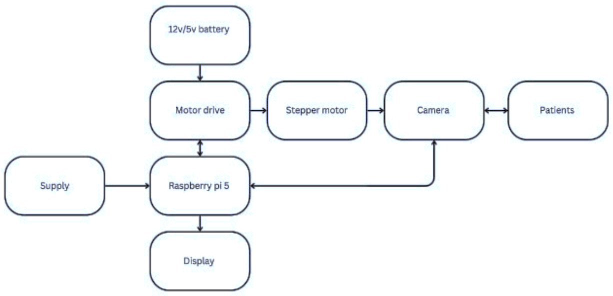

Figure 1- Block diagram of the proposed system

In comparison, the proposed system employs Raspberry Pi with a camera module for image acquisition, cloud-based deployment of deep learning models (VGG-16, Res-Net, Dense-Net), and Flask integration for API communication. These features enable seamless data transfer and real-time predictions, distinguishing it from static, device-dependent systems. Additionally, the use of TensorFlow Lite for lightweight model inference ensures compatibility with low-resource environments, while SQLite facilitates efficient data storage and retrieval for user interfaces.

The proposed solution offers competitive accuracy in lesion detection, leveraging the strength of pre-trained CNN models and transfer learning, as evidenced in the literature. However, challenges persist, such as the requirement for consistent internet connectivity, the need for robust security measures to handle patient data, and performance optimization for varying image qualities. By addressing these gaps, the system demonstrates significant potential to complement existing diagnostic methods and expand access to early cancer detection.

6. FUTURE DIRECTION

- Multi-Disease Detection: Expanding the system to detect other oral diseases, such as periodontal issues or dental caries, alongside cancer detection.
- Interdisciplinary Collaboration: Encouraging collaboration between clinicians, AI researchers, and policymakers to refine diagnostic systems and address ethical considerations.
- Longitudinal Studies: Conducting studies that track patient outcomes to validate the clinical impact of these systems over time.
- Cost Optimization: Focusing on further reducing the cost of hardware and software to make the system more accessible in low-income regions.
- Integration with Wearable Devices: Exploring the potential for wearable oral health monitoring devices that complement the primary diagnostic system.

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7. CONCLUSION:

Oral cancer remains a significant global health challenge, with early detection being critical to improving survival rates and patient outcomes. This project combines advanced deep learning models such as VGG-16, Res-Net, and Dense-Net with Io T-enabled hardware like Raspberry Pi, Stepper motor and a camera module to create a cost-effective and efficient diagnostic system. By leveraging cloud-based processing and Flask API's for seamless integration, the system ensures real-time image analysis and predictive results, which are accessible via a user-friendly web application. The integration of TensorFlow Lite enhances the scalability and adaptability of the solution, while the use of SQLite ensures lightweight and efficient data management. This innovative approach addresses critical challenges in oral cancer detection, such as affordability, accessibility, and diagnostic accuracy. However, limitations such as dataset's diversity, model robustness, and privacy concerns highlight areas for further research and development. This study underscores the trans-formative potential of AI and Io T in healthcare, offering a promising path toward reducing the burden of oral cancer, particularly in resource-limited settings. Future efforts should focus on refining the system, expanding its capabilities, and addressing challenges to ensure widespread adoption and impact in real-world clinical scenarios.

References

[1] K. Mustafa, S. Yang, et al., "Self-calibration of a biologically inspired 7 DOF cable-driven robotic arm," IEEE/ASME Transactions on Mechatronics, vol. 13, no. 1, pp. 1–10, 2008.

[2] H. S. Kim, J. K. Min, et al., "Multiple-Degree-of-Freedom Counterbalance Robot Arm Based on Slider-Crank Mechanism," IEEE Transactions on Robotics, vol. 32, no. 1, pp. 1–15, 2016.

[3] A. S. Patil, R. S. Chauhan, and S. B. Mehta, "Deep Learning for Oral Cancer Diagnosis and Management: Current Trends and Future Directions," Journal of Cancer Research and Clinical Oncology, 2024.

[4] N. B. R., G. Kiran, and S. M. P., "Oral Cancer Detection Using Machine Learning and Deep Learning Techniques," International Journal of Current Research and Review, vol. 12, no. 2, pp. 15–22, 2024

[5] G. Kavya, K. M. Devi, R. Ashwini, M. Priscilla, and R. S. Vijayashanthi, "Oral Cancer Detection Using CNN," International Journal of Creative Research Thoughts (IJCRT), vol. 11, no. 3, pp. 45–52, 2023.

[6] V. P. Veeraraghavan, S. Daniel, A. K. Dasari, K. R. Aileni, C. Patil, and S. R. Patil, "Harnessing Artificial Intelligence for Predictive Modelling in Oral Oncology: Opportunities, Challenges, and Clinical Perspectives," Journal of Oncology, vol. 15, no. 2, pp. 35–42, 2024

[7] M. A. Deif, H. Attar, A. Amer, I. A. Elhaty, M. R. Khosravi, and A. A. A. Solyman, "Diagnosis of Oral Squamous Cell Carcinoma Using Deep Neural Networks and Binary Particle Swarm Optimization on Histopathological Images: An AIoMT Approach," Hindawi Computational Intelligence and Neuroscience, 2022

[8] R. Reethu, D. Preetha, P. Parameshwaran, C. B. Sivaparthipan, and T. Kalaikumaran, "A Design of Smart Device for Detection of Oral Cancer Using IoT," Proceedings of International IoT Conference, pp. 155–162, 2023

[9] K.-S. Hwang, J. L. Lee, and W. C. Jiang, "Intelligent Image Base Visual Servoing Controller for Robot Arm," Proceedings of IEEE Robotics Conference, pp. 122–130, 2017.

[10] S. Yeotikar, A. M. Parima, and Y. V. D. Rao, "Automation of End Effector Guidance of Robotic Arm for Dental Implantation Using Computer Vision," Journal of Automation and Robotics, vol. 15, no. 4, pp. 25–35, 2016

[11] K. K., K. B. M., and S. Lakshminarayanan, "Design and Development of a Robotic Arm," International Journal of Robotics and Automation Engineering, vol. 8, no. 2, pp. 10–20, 2016

[12] R. Szabo and A. Gontean, "Industrial Robotic Automation with Raspberry Pi Using Image Processing," Proceedings of International Robotics Conference, pp. 45–52, 2016

[13] A. B. Therese and P. Gupta, "Robotic Arm with Real-Time Image Processing Using Raspberry Pi, Both Automated and Manually," International Conference on Robotics and Automation, pp. 90–95, 2018

[14] I. Ahmad and F. Alqurashi, "Early Cancer Detection Using Deep Learning and Medical Imaging: A Survey," Critical Reviews in Oncology/Hematology, vol. 125, pp. 10–25, 2024

[15] Q. Huang, H. Ding, and N. Razmjooy, "Oral Cancer Detection Using Convolutional Neural Network Optimized by Combined Seagull Optimization Algorithm," Biomedical Signal Processing and Control, vol. 25, pp. 125–135, 2024.

[16] P. Hemalatha, C. K. H. Lakshmi, and S. A. K. Jilani, "Real-Time Image Processing Based Robotic Arm Control Standalone System Using Raspberry Pi," Proceedings of International Conference on Automation, pp. 110–115, 2015.

[17] R. Yadav, P. Ujjainkar, and R. Moriwal, "Oral Cancer Detection Using Deep Learning Approach," 2023 IEEE International Students' Conference on Electrical, Electronics, and Computer Science (SCEECS), pp. 52–57, 2023

[18] S. Krishna, J. Lavanya, G. Kavya, N. Prasamya, and Swapna, "Oral Cancer Diagnosis Using Deep Learning for Early Detection," 2022 International Conference on Electronics and Renewable Systems (ICEARS), pp. 101–108, 2022.

[19] S. Krishna, J. Lavanya, G. Kavya, N. Prasamya, and Swapna, "Oral Cancer Diagnosis Using Deep Learning for Early Detection," 2022 International Conference on Electronics and Renewable Systems (ICEARS), pp. 101–108, 2022.

[20] L. Li, C. Pu, J. Tao, L. Zhu, S. Hu, B. Qiao, L. Xing, B. Wei, C. Shi, P. Chen, and H. Zhang, "Development of an Oral Cancer Detection System Through Deep Learning," BMC Oral Health, vol. 24, no. 1468, pp. 1–10, 2024

[21] M. A. Elaziz, A. Dahou, A. Mabrouk, R. A. Ibrahim, and A. O. Aseeri, "Medical Image Classifications for 6G IoT-Enabled Smart Health Systems," Diagnostics, vol. 13, no. 834, pp. 1–26, 2023.

[22] Shafi, M. Sajad, A. Fatima, D. G. Aray, V. Lipari, I. de la Torre Diez, and I. Ashraf, "Teeth Lesion Detection Using Deep Learning and the Internet of Things Post-COVID-19," Sensors, vol. 23, no. 6837, pp. 1–20, 2023.