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SKIN CANCER DETECTION MODEL USING MACHINE LEARNING ALGORITHM

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Abstract
One of the most commonly diagnosed cancer, universally is the skin cancer. New cases are reported in millions on yearly basis. There are different types of skin cancer such as: melanoma, basal cell carcinoma, and squamous cell carcinoma and each of them with varying degrees of seriousness. Of all of the types mentioned above melanoma is the deadliest of them if not detected and treated on time. Conventional method of diagnosing skin cancer is usually carried out using manual inspection by the dermatologist, this is followed by biopsies and histopathological analysis. While these methods are good, they consume so much of time, expensive and not easily accessible especially from the remote areas. Advancement in the technology of Artificial Intelligence (AI) especially in Machine Learning and Deep Learning has brought on board the possibility of medical image analysis. Convolutional Neural Network (CNN) is one of the most effective Deep Learning models for image recognition. This is because it has the capacity to automatically extract features from raw image data. The research is concerned with the development of skin cancer detection model based on Convolutional Neural Network to identify and classify skin lesions. The system is trained using dataset obtained from International Skin Imaging Collaboration (ISIC) archive, which host large amount of skin images. The model is designed to map out the differences between cancerous and non-cancerous lesions by learning patterns like asymmetry, texture, colour variations and irregularities within the borders. Results shows that the model is accurate in the cases of skin cancer detection and can be useful to dermatologist as a tool for early diagnosis.

Keywords: Cancer, melanoma, Carcinoma, Convolutional Neural Network, Machine Learning, Deep Learning, Lesions, Asymmetry and Diagnosis.

1. Introduction

According to World Cancer Research Fund, (2022) there were more than 330,000 new cases of skin cancer worldwide, making it the 17th most common type of cancer Skin cancer, consisting melanoma and non-melanoma types. Matter of fact, the incidence rates vary significantly across

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regions, with higher occurrences in countries like Australia and New Zealand, attributed to factors such as fair skin prevalence and high ultraviolet (UV) radiation exposure.

Skin cancer has been linked to increased exposure to UV radiation, both from natural sunlight and artificial sources like tanning beds. Factors like outdoor activities without adequate sun protection, contribute to this trend. Skin Cancer Foundation, 2022 states that, environmental changes leading to ozone layer depletion have intensified UV radiation levels, making it even more risky. Early detection of skin cancer is very important for effective treatment and improved survival rates. Verma & R, (2023) states that, traditional diagnostic methods rely heavily on visual inspections and biopsies performed by dermatologists. Furthermore, these methods can be subjective and may lead to inconsistency in diagnoses. Limited access to specialized healthcare services in certain regions poses challenges for timely and accurate detection. Progress made so far in machine learning (ML) and deep learning (DL) have opened new chapters for advancing skin cancer detection using medical images. ML algorithms, particularly convolutional neural networks (CNNs), have demonstrated high accuracy in classifying skin lesions. These technologies offer the potential for automated, consistent, and early diagnosis, which is especially beneficial in resource-limited settings. Integrating ML-based diagnostic tools into clinical practice could augment dermatologists' capabilities, leading to better patient outcomes (Mahmud et al., 2023).

2. Literature Review

Akter et al. (2024) proposed a hybrid deep learning model by integrating InceptionV3 and DenseNet121. Their system used hybrid feature fusion and achieved an accuracy of 92.27%, demonstrating effectiveness in distinguishing between benign and malignant lesions. However, the method required substantial computational power, making it less ideal for low-resource settings. A challenge at the 2017 International Symposium on Biomedical Imaging (ISBI)," hosted by the International Skin Imaging Collaboration (ISIC). Published in the proceedings of the 2018 IEEE 15th International Symposium on Biomedical Imaging, the study focused on evaluating algorithms for skin lesion analysis to facilitate melanoma detection. This challenge provided researchers with a standardized dataset and evaluation metrics, fostering advancements in automated melanoma detection using machine learning techniques (Codella et al., 2018). Lee et al., (2020) stated that transfer learning has been widely adopted to enhance skin cancer classification, especially when dealing with limited datasets. Le et al. (2020) utilized an ensemble of modified ResNet50 models, incorporating class-weighted and focal loss functions, to classify skin lesions into seven categories using the HAM10000 dataset. Their approach achieved top-1 accuracy of 93%, demonstrating the effectiveness of transfer learning in medical image classification.

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Shen et al. (2021) conducted a comprehensive study on the application of deep learning in medical image analysis. Their research focused on how Convolutional Neural Networks (CNNs) have been effectively used in various tasks like image classification, segmentation, detection, and registration. They highlighted that deep learning has shown great success in analyzing radiology images, pathology slides, and dermatological conditions. However, they pointed out challenges such as limited availability of annotated medical datasets, the "black box" nature of deep learning models, and the difficulty in deploying models in clinical settings. They also emphasized the importance of model interpretability and regulatory approval before clinical use.
In recent years, CNN-based approaches have emerged as powerful tools in the field of skin cancer diagnosis, offering automated and objective methods for lesion classification. Convolutional Neural Networks (CNNs) excel at extracting hierarchical features from images, allowing them to discern subtle patterns indicative of malignancy. Esteva et al. (2017) showcased the potential of CNNs to achieve dermatologist-level accuracy in classifying skin lesions, marking a significant advancement in automated diagnostic capabilities. The success of CNN-based approaches in skin cancer diagnosis has been attributed to their ability to learn complex features directly from raw pixel data. Unlike traditional methods that rely on human interpretation, CNNs can automatically extract relevant features from images, enabling objective and standardized assessment. CNN architectures such as ResNet, Inception, and DenseNet have been widely adopted and fine-tuned on large datasets such as the ISIC archive, further enhancing their performance. Gu et al., (2018) indicated that despite their successes, CNN-based approaches are not without limitations.

They often require large amounts of annotated data for training, which can be challenging to obtain in medical imaging domains. Additionally, CNNs may struggle with capturing long-range dependencies within images, particularly in cases where lesions exhibit complex and heterogeneous features. Dosovitskiy et al., (2020) stated that there is an ongoing research into alternative architectures, such as Vision Transformers (ViTs), which offer the potential to overcome these limitations and further improve diagnostic performance. According to dosovitskiy et al. (2020) vision transformers (ViTs) have recently emerged as a novel approach to image classification, demonstrating promising results in various domains, including medical imaging. Touvron et al., (2021) further advanced ViTs' performance in image classification tasks, demonstrating their efficacy in achieving competitive results with significantly fewer parameters than CNNs.

3. Materials and Methods

3.1 Functional Requirements:

Functional requirements are based on stakeholder inputs during systems analysis. These includes the ability to classify different types of skin lesions (e.g., melanoma, basal cell carcinoma),

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providing probability scores for each classification, and supporting various image formats and resolutions. Image Classification: The system must accurately classify skin lesion images into categories such as melanoma, basal cell carcinoma, squamous cell carcinoma, and benign lesions, providing probability scores or confidence levels for each classification to aid medical professionals in making informed decisions during diagnosis. Accuracy and Performance: The system should achieve a classification accuracy of at least 90% using standard evaluation metrics like sensitivity and specificity. It must also ensure efficient inference times to support real-time or near real-time diagnosis in clinical settings, thereby enhancing the speed and accuracy of medical assessments. Compatibility and Integration: The system needs to support a wide range of image formats commonly used in dermatology, including high-resolution medical imaging formats. Scalability: The system should handle the continuous growth of its skin lesion image dataset without compromising performance or accuracy. It must also scale effectively to meet increased usage and demand as it is deployed and utilized across various clinical settings, ensuring reliable and efficient diagnostic capabilities.

User Interface: The system should feature an intuitive and user-friendly interface specifically designed to meet the workflow needs of dermatologists and medical professionals

3.2 Non-Functional Requirements:

Capture non-functional requirements such as performance metrics (e.g., classification accuracy, inference time), scalability (supporting a growing dataset), security (data encryption, access controls), and usability (intuitive interface for medical professionals).

Performance: The system must provide rapid results for individual image classifications, ensuring that diagnostic outcomes are available within seconds to support timely clinical decisions.

Security and Privacy: To safeguard patient data, the system must adhere to healthcare data privacy regulations such as Health Insurance Portability and Accountability Act (HIPAA) and General Data Protection Regulation (GDPR). This includes implementing strong data encryption measures for transmission and storage, along with access controls and audit logs to monitor and manage access to sensitive medical information, ensuring confidentiality and compliance with regulatory standards.

Reliability: The system should maintain high availability with minimal downtime to ensure uninterrupted access to diagnostic capabilities for healthcare providers.

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Usability: For ease of use by medical professionals, the system should offer comprehensive documentation and training resources. It should feature an intuitive user interface designed to minimize cognitive load and facilitate rapid interpretation of diagnostic results, enhancing user efficiency and satisfaction during clinical use.

Ethical Considerations: The system must include mechanisms for obtaining patient consent for the use of medical images in research and diagnostic procedures, respecting ethical guidelines and patient rights.

Regulatory Compliance: Adherence to regulatory requirements for medical software applications is essential. This includes obtaining necessary certifications applicable to the jurisdiction and regularly updating the system to incorporate changes in regulatory standards and best practices in medical image analysis, ensuring ongoing compliance and quality assurance.

3.3 Method of Data Collection

There are different methods of data collection but the method of data collection used in this work is Documentation Method.
The documentation method is a secondary method of data collection. This method involves the use of journals, handbooks, newspapers and projects. This method was used because, it serves as the basis of reference to existing research work. It includes the following:

Publicly Available Datasets: Utilize established datasets such as the International Skin Imaging Collaboration (ISIC) archive, which contains a large collection of dermoscopic images of skin lesions. These datasets are valuable as they are widely used in research and benchmarking, providing a diverse range of labelled images.

Medical Institutions: Collaboration with hospitals, dermatology clinics, and research institutions to collect real-world patient data. This collaboration can have helped in gathering a variety of skin lesion images under controlled and annotated conditions.

3.4 Design Considerations

3.4.1 Architectural Design

The architectural design of the skin cancer diagnosis system is meticulously crafted to ensure robustness, scalability, security, and seamless integration. The system adopts a modular, layered architecture comprising distinct components for data ingestion, pre-processing, model training and inference, integration, and user interaction. The data ingestion layer integrates multiple data sources, including public datasets and hospital databases, using secure application programming

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Interface (API) to ensure standardized data transfer. Raw and pre-processed images are stored in a centralized, secure database. The pre-processing layer enhances image quality and diversity through modules for cleaning, normalization, and augmentation. In the model training and inference layer, deep learning models like Visual Geometry Group (VGG) and ResNet are stored in a model repository, trained using high-performance computing resources, and optimized for accuracy and efficiency. The inference engine provides real-time and batch processing capabilities, delivering classification results with confidence scores. The integration layer ensures compatibility with electronic health record (EHR) systems and adheres to healthcare data exchange standards such as HL7 and FHIR, facilitating easy access to patient data and consistent data communication.

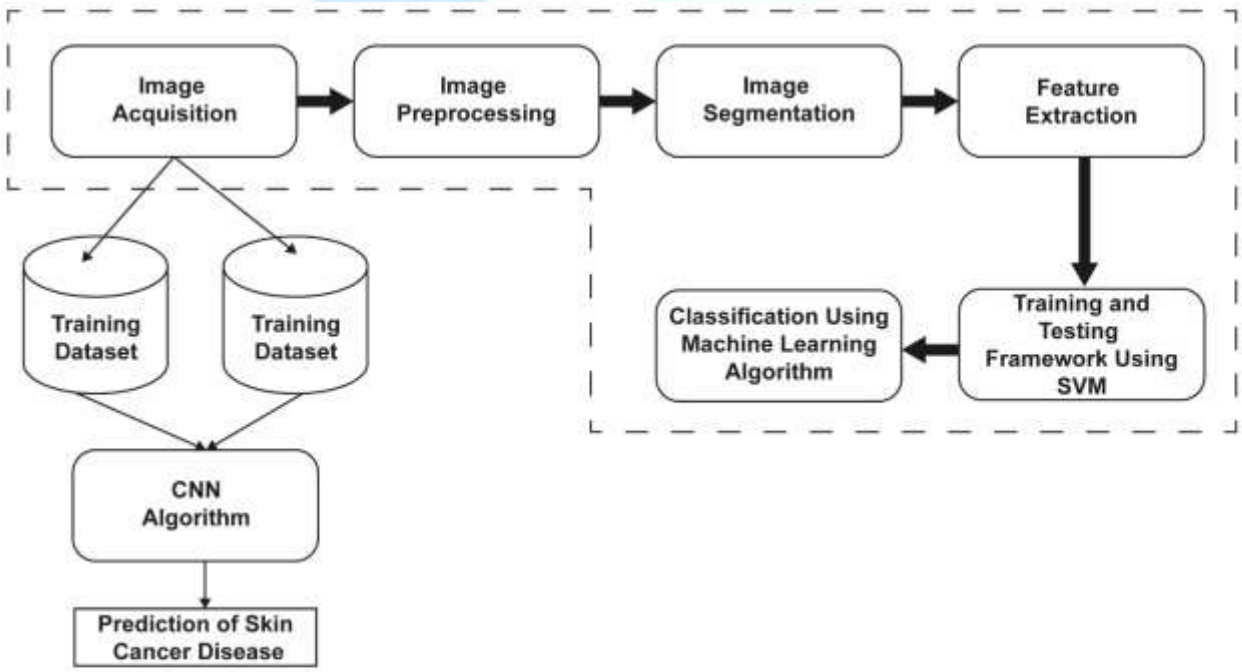

Figure 3.1: Architectural Design

3.4.2 Use Case Diagrams

The architectural design of the skin cancer diagnosis system includes multiple actors and use cases, ensuring comprehensive and efficient operation. Dermatologists interact with the system by uploading dermoscopic images, which the AI model classifies into various types of skin lesions. The system then generates diagnostic reports that dermatologists can view and annotate for further analysis. System administrators manage user accounts, perform data backups, and monitor system performance to ensure reliability and security. Patients review and provide consent for the use of their images, maintaining ethical standards. The system also integrates seamlessly with electronic health record (EHR) systems, allowing for the efficient fetching and storing of patient data, which supports real-time clinical decision-making. This integrated approach ensures that the system is user-friendly, secure, and scalable, facilitating accurate and timely skin cancer diagnosis.

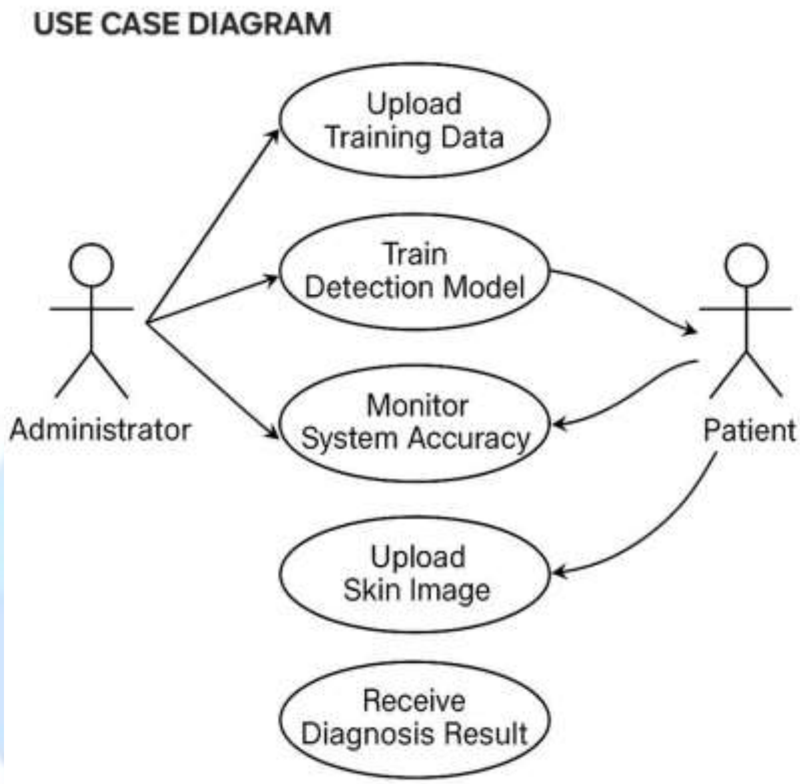

Figure 3. 2: Use Case Diagram

3.4.3 User Interface Design

The user interface (UI) design for this project aims to provide an intuitive, user-friendly experience tailored to the needs of dermatologists and medical professionals. Here’s a breakdown of the UI components and their functionalities:

Home Screen

1. Navigation Bar: Provides easy access to different sections of the application such as Home, Upload Image, Diagnostic Reports, and Settings.
2. Dashboard: Displays an overview of recent activities, system status, and quick links to key functionalities.

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Figure 3. 3: Skin Cancer Detection Application

3.5 Computing Resources

Computing resources requirement is a combination of hardware and software components that makes work to be carried out. The system requirement for this research work is subdivided into Hardware and Software.

3.5.1 Hardware Requirements

Hardware is the computer equipment and devices that are involved in the function of a computer system together with the software components. Hardware are the physical components of the computer system assembled together to interact with the software in order to form a composite system. The minimum hardware requirements are:

1. CPU Pentium III (886 MHz) processor
2. 100MB available disks space
3. RAM (256MB)
4. 14’SVGA Colored Monitor
5. U.P.S 650va (uninterruptible power supply)
6. Hard Disk Drive (HDD) of 60GB

3.5.2 Software Requirements

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Operating System:

1. Server: Windows Server
2. Client: Windows, macOS, or Linux

3.5.3 Frameworks and Libraries:

1Deep Learning Frameworks: Tensorflow, Keras, PyTorch
Image Processing Libraries: OpenCV, PIL (Python Imaging Library)
Web Framework: Flutter
Database: MySQL for storing images and metadata

Programming Languages:

1. Backend Development: Python (Flask)
2. Frontend Development: React with Material UI

APIs:

1. RESTful APIs: For communication between the client and server
2. Integration APIs: For connecting with Electronic Health Record (EHR) systems, such as HL7 or FHIR

Security Tools:

1. Encryption Libraries: OpenSSL for data encryption
2. Authentication Frameworks: OAuth 2.0, JWT (JSON Web Tokens) for secure authentication

4.1 Implementation and Evaluation

This chapter covers the implementation details of the Skin Cancer Classification System, including the tools and technologies used, the architecture of the system, and the evaluation of the system's performance. The implementation involves setting up the environment, developing the model, and creating the user interface. The evaluation focuses on assessing the accuracy and effectiveness of the system using various metrics.

4.1.1 System Testing and Evaluation

The testing and evaluation phases of the work involved thorough assessments across performance, usability, reliability, and security aspects. Performance testing, conducted using tools like Apache JMeter, verified the system's ability to handle concurrent requests efficiently, maintaining swift response times under varying loads. Usability was evaluated through user surveys and interviews, highlighting the system's intuitive interface and effectiveness for recommendations. Reliability testing ensured consistent and accurate recommendations across different scenarios, bolstering confidence in its practical application.

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4.1.2 System Conversion Plan

The system conversion plan for the crop recommendation system adopts a parallel changeover approach, where both the new system and existing methods will operate concurrently and undergo testing over a period of three to six months. This approach allows for thorough validation of the new system's functionality and performance while mitigating risks associated with potential errors or discrepancies. By running both systems in parallel, we aim to ensure a seamless transition and validate that the new system meets all specified requirements and effectively supports medical decision making functions.

This approach does not only facilitates thorough testing and error identification but also ensures stakeholder confidence in the reliability and functionality of the implementation strategies.

well as its implementation are explained.

4.1.3 System and Database Installation

After the system has been tested for some period, and found to be working smoothly as expected, the system was ready for Installation and Implementation.

Installing the Program Folder/Files (Minimum of Windows XP or higher version OS).

1. Install Node.js.
2. Install Python.
3. Install Xampp set up a MySQL Atlas account.
4. Install Git.

Steps to Install

1. Clone the repository.
2. Navigate to the backend directory and install dependencies.
3. Create a .env file in the backend directory and add environment variables.
4. Navigate to the frontend directory and install dependencies.
5. Start the backend server.
6. Start the Python application.

Running the Software System

Start the Backend Server:

1. Navigate to the backend directory.
2. Ensure your Xampp(Apache and MySQL) instance is running.
3. Start the Express.js server.

Start the Frontend Application:

1. Navigate to the frontend directory.
2. Open the project using VS Code.
3. Start the react application.

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Figure 4.1: Program Sample Output

Figure 4.2: Classification page

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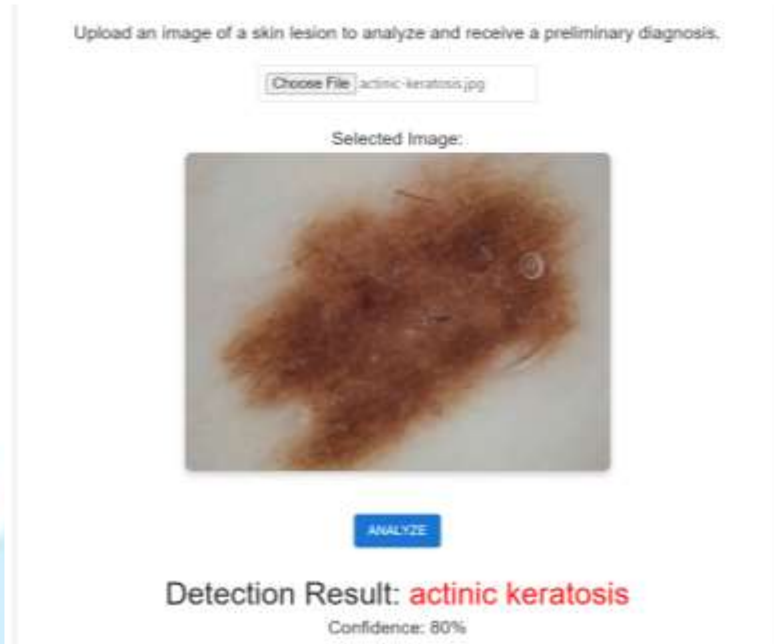

Figure 4.3: Skin Cancer Classification result

Figure 4.4: Sample Skin Cancer Images

5. Discussion

The work resulted into the development of skin cancer classification system using deep learning algorithm to detect and classify skin lesions from images. Dataset of skin lesions was collected, prprocessed and used to train a convolutional neurak network (CNN) model.
The system after implemetation, is now functionong and allowing users to upload images for rea-time classification. The performance of the model was evaluated using metrics of accuracy, precision and recall indicating promising output in ditingushing between malignant and benign lesions. The model is developed to help health care providesrs or professionals as a supplimentary tool for early detection of cancer cases.

5.1 Conclusion

The skin cancer classification system successfully demonstrated the potential of deep learning in medical image analysis, specifically in detecting skin cancer. By leveraging a CNN-based model, the system achieved a high level of accuracy and can significantly reduce diagnostic errors. While the results are promising, further refinement and larger datasets are required to improve the system's robustness and generalizability. Ultimately, this work contributes to the growing field of AI-powered healthcare tools and highlights the need for continued research to fully realize its clinical potential.

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