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Design and Implementation of a Web-Based Deep Learning System for Melanoma Detection Utilizing the Inception Model

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Abstract - *Melanoma represents a particularly aggressive form of skin cancer, necessitating prompt detection to mitigate mortality rates and minimize the invasiveness of treatment. Contemporary advances in computer-aided diagnosis (CAD) have leveraged sophisticated imaging techniques to enhance early-stage diagnosis of skin malignancies. This research aims to construct a web-based platform for the automated analysis of dermoscopic images to ascertain early melanoma presence. The implementation employs the Inception V3 model, a Convolutional Neural Network (CNN) architecture renowned for its efficacy in image classification tasks, specifically in medical imaging domains such as dermoscopy. This model facilitates the processes of image acquisition, preprocessing, segmentation, feature extraction, and classification. The web application, developed using Python, HTML, and CSS, showcases a streamlined interface for clinical application. Empirical evaluations reveal that the model achieves an accuracy range of 90-93%, underscoring its potential utility in clinical settings. This platform empowers users to swiftly identify skin abnormalities, thereby enhancing early diagnosis and preventive care, significantly contributing to advancements in dermatological oncology.*

Key Words: Convolutional Neural Network (CNN), Computer-aided diagnosis (CAD), Dermoscopic images, Empirical evaluations, Image classification, Inception V3 model, Melanoma

1. INTRODUCTION

Melanoma is recognized as the deadliest form of skin cancer, with significant global impact. It has been reported recently that new melanoma cases reported in 2020 was 325,000 may increase up to 510,000 by 2040. Likewise, deaths due to melanoma may rise by approximately 68%, from 57,000 in 2020 to 96,000 in 2040[1].

Early detection of melanoma can lead to a complete cure through simple excision of the malignant tissue. However, late-stage detection often results in metastasis, leading to a poor prognosis [2]. Melanoma originates in melanocytes, the skin cells responsible for producing pigments that determine skin color. The patterns of melanoma occurrence vary geographically; in Western countries, melanomas typically arise in sun-exposed areas such as the chest, forehead, and limbs. Conversely, in Asia, melanomas more commonly develop on the hands and feet, which are less exposed to the sun, as well as on mucous membranes, including the lining of the mouth, throat, gastrointestinal tract, and the vaginal tract in women [4].

Excessive exposure to ultraviolet (UV) radiation from sunlight or artificial tanning is a major risk factor for the development of melanoma. Reducing UV exposure can significantly lower the risk of melanoma, achievable through measures such as consistent use of sunscreen, wearing long-sleeved clothing, and using hats to block the sun. Additionally, genetic mutations in cancer-causing genes, particularly BRAF and NRAS, CDKN2A, play a crucial role in melanoma development [2][4].

In the past decade, malignant melanoma has become one of the most dangerous cancers, spreading rapidly worldwide. Each year, more than one million cases of non-melanoma skin cancer and over 250,000 cases of melanoma are reported [2]. In the United States, melanoma was ranked fifth for expected new cancer cases in both males and females in 2019 **Error! Reference source not found.**. The incidence of melanoma in the U.S. has exhibited a concerning upward trend, significantly contributing to cancer-related mortality over the past decades. To address this, a web-based deep learning system has been developed for melanoma detection, employing the Inception model to achieve faster operation and higher accuracy. In response, a sophisticated web-based deep learning system using the Inception model has been developed, offering rapid and highly accurate melanoma detection with innovative approach aims to enhance early diagnosis.

1.1 Background

Before Skin cancer, particularly melanoma, represents a pressing global health concern. A new study by scientists from the International Agency for Research on Cancer (IARC) and partners predicts that the number of new cases of cutaneous melanoma per year will increase by more than 50% from 2020 to 2040. The study, published in the journal JAMA Dermatology, provides global patterns of cutaneous melanoma in 2020 as well as projections of the numbers of new cases and deaths for 2040 [7].

Early detection plays a pivotal role in addressing this challenge. It has been acknowledged that localized melanoma boasts a remarkable five-year survival rate of 95%. Furthermore, it exhibits more aggressive behavior in transplant recipients, with a higher risk of metastasis and mortality. This stark contrast emphasizes the urgent need for accurate and efficient detection methods [8].

However, the intricacies of melanoma pose substantial diagnostic challenges. Research reveals significant variations in dermatologists' diagnostic accuracy, with sensitivity rates for early-stage melanomas up to 78.3%. Such discrepancies underscore the necessity for a standardized, technology-driven approach [9].

The impact of melanoma is further highlighted by its potential for morbidity and mortality. Although melanoma accounts for only about 1% of skin cancer cases, it is responsible for a significant portion of skin cancer-related deaths. In the United States, for instance, it is estimated that in 2019, about 7,410 people died to melanoma. Early detection and timely treatment are crucial factors in improving outcomes. The five-year survival rate for localized melanoma is impressively high at around 95%. However, when melanoma progresses to advanced stages and spreads to distant organs, the five-year survival rate drops dramatically [8]. This underlines the importance of not only raising awareness about the risks of melanoma but also implementing effective prevention strategies and early detection measures.

Considering the current scenario in this field of research this research is devoted to provide cutting-edge artificial intelligence techniques to facilitate melanoma detection. By harnessing the power of machine learning, aim of this research is to establish a consistent, accurate, and efficient method for identifying and classifying melanoma lesions. This approach has the potential to facilitate early intervention and significantly improve patient outcomes in the battle against this formidable disease. The foundation of this research work is rooted in statistical data, reflecting the urgency and potential of the proposed innovative approach to revolutionize melanoma detection.

1.2 Programming Techniques

This section presents the details description of different models and techniques with their process of integration with AI technology involved in the research methodology.

Application of Deep Learning Models

Deep Learning models have revolutionized various fields by learning complex patterns from raw data. In computer vision, they excel in image classification, object detection, and image segmentation, with applications like facial recognition and medical diagnostics. In Natural Language Processing (NLP), models such as Recurrent Neural Networks (RNNs) and Transformers have transformed tasks like sentiment analysis and language translation. In healthcare, Deep Learning enhances medical imaging for early disease detection and drug discovery. Autonomous systems, like self-driving cars, also benefit from these models for real-time decision-making. Additionally, digital platforms utilize Deep Learning for personalized recommendation systems.

Integration of AI Techniques

AI, particularly Deep Learning, has significantly improved melanoma detection. Convolutional Neural Networks (CNNs) analyze dermatoscopic images to identify melanoma, aiding early detection and enhancing diagnostic accuracy. These models provide robust support to dermatologists, offering reliable second opinions. However, their efficacy depends on high-quality data, meticulous annotation, and ethical considerations [10][11].

Integration of Machine Learning Techniques

Machine learning techniques, such as transfer learning with models like Inception V3, are crucial for melanoma detection. Transfer learning leverages pre-trained models, reducing training time and optimizing resources. Data augmentation techniques expand datasets, enhancing model generalization and classification accuracy for various skin diseases.

Integration of Deep Learning Techniques

Deep Learning, especially CNNs, has redefined melanoma detection by extracting complex features from medical images. Techniques like transfer learning and data augmentation enhance model performance and adaptability [12]. This integration promises earlier detection, reduced false negatives, and personalized treatment strategies, advancing melanoma diagnosis and patient care.

1.3 Objective

Deep learning (DL) involves computer algorithms that improve automatically through experience and data, building models based on training data to make predictions or decisions without explicit programming. DL is used in various applications, enabling computers to perform tasks by learning from provided data. While simple tasks can be programmed step-by-step, advanced tasks require DL models **Error! Reference source not found.**. DL is the most important part of the program as it dictates creating the backbone of the interface.

For studying image classification with DL, the following steps are involved:

1. Developing the Inception Model using machine learning algorithms,
2. Selecting melanoma data for implementation,
3. Applying Inception for hyper-parameter tuning, and
4. Validating the model with melanoma data.

1.3 Significance and goals

Deep learning algorithms, a subset of machine learning techniques, have revolutionized numerous fields by enabling computers to learn patterns directly from data. These algorithms, based on artificial neural networks designed to simulate the human brain's structure, excel at automatically learning hierarchical data representations through multiple layers, or "deep" architectures. This capability allows deep learning algorithms to perform tasks such as image and speech recognition, language translation, and strategic game playing with state-of-the-art performance. Convolutional Neural Networks (CNNs) are particularly effective for image-related tasks, while Recurrent Neural Networks (RNNs) are suited for sequence data like language.

Despite their impressive achievements, deep learning algorithms require substantial computational resources and extensive datasets. Continuous advancements are enhancing their efficiency and applicability, solidifying their role in shaping modern AI capabilities.

This research work aims to leverage these advancements to improve melanoma skin malignancy classification. The dataset includes two classes: melanoma and non-melanoma**Error! Reference source not found.**. Using the publicly accessible ISIC database for training and testing images, the AI architecture Inception V3 was employed to train the dataset. Unlike previous studies that compared melanoma with specific or other skin-related datasets, this approach includes all other skin-related diseases as non-melanoma for comprehensive comparison and improved accuracy. This method aims to distinguish melanoma from other skin diseases.

This significance of this research lies in its potential to enhance melanoma detection accuracy, improving early diagnosis and treatment outcomes. The primary objectives are to develop an AI-based framework for testing melanoma skin diseases, discuss the challenges melanoma poses, explore preventive measures, and highlight proposed solutions by various researchers. The methodology, materials, and results obtained are detailed, culminating in an evaluation of the system and its outcomes.

2. Methodology

This research work follows a structured and iterative development approach. The methodology includes collecting a melanoma detection dataset from Kaggle, splitting it into training and testing sets, and cleaning the training data. The Inception deep learning model is then imported and trained using the prepared data. The model's accuracy is tested with the test data, and the results are analyzed using a confusion matrix. The system design encompasses data preprocessing, encoding, feature selection, model training, and evaluation, highlighting its advantages, disadvantages, and features [12].

2.1 Workflow Diagram

This diagram provides a detailed overview of the program's architecture and the user-admin interface specifically designed for melanoma detection. It showcases the structural components and the interaction flow between the user and administrative functionalities, highlighting how the system facilitates efficient and accurate melanoma detection.

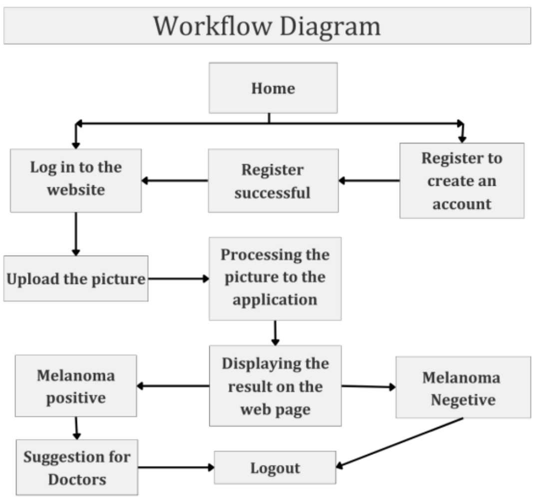

Figure 1: Workflow diagram of melanoma detection program

The interface diagram is intentionally kept simple to ensure comprehensibility for all users, given its role in handling medical data within a data science framework.

2.2 User and Interface

Melanoma Detection Application

The application features two primary roles: "User" and "Admin."

User Interactions:

- **Login:** Secure access to personalized accounts.

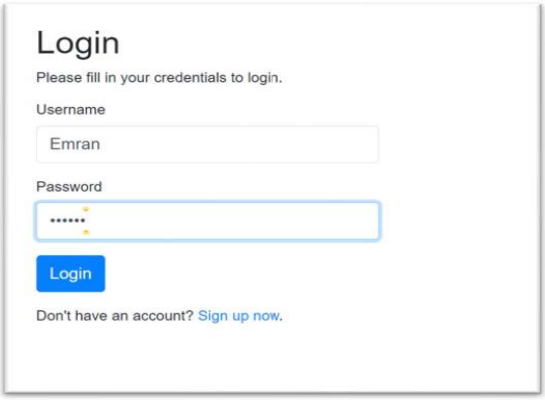

Figure 2: User login Page of the website

- **Registration:** Create new accounts.

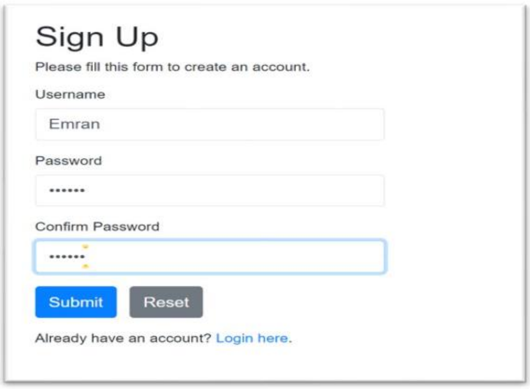

Figure 3: User sign up page of the website

- **Interact with Blog:** Explore melanoma awareness content.

- **Access Detection Service:** Utilize melanoma detection functionality.

Figure 4: Picture upload page of the website

- **Browse Gallery:** View images to aid visual understanding.

- **Explore About Us:** Learn about the application's mission and purpose.

- **Positive Detection:** Receive doctor suggestions if melanoma is detected.

Admin Interactions:

- **Login:** Authenticate to access the admin panel.

- **Manage Blogs:** Create and update blog content.

- **Gallery Management:** Maintain and update image galleries.

- **Positive Detection Support:** Provide doctor suggestions for positive detections

2.3 Data Management

2.3.1 Data Collection

The datasets used in this study are sourced from Kaggle, comprising information on 1180 patients aimed at identifying Pulmonary Abnormalities. The dataset includes 16 different attributes per patient. Of the patients, 34.7% are classified as Normal, while 65.3% exhibit Pulmonary Abnormalities. The dataset is divided into training (80%) and testing (20%) sets. The table provides a sample of the dataset, listing the attributes and their respective scope.

Figure 5 shows the sample of the table with the attributes and the possible scope of the dataset.

```
# Importing the Training Dataset
df_train = pd.read_csv("../input/jpeg-melanoma-384x384/train.csv")
df_train.head()
```

	image_name	patient_id	sex	age_approx	anatom_site_general_challenge	diagnosis	benign_malignant	target	tfrecord	width	height
0	ISIC_2637011	IP_7279968	male	45.0	head/neck	unknown	benign	0	0	6000	4000
1	ISIC_0015719	IP_3075186	female	45.0	upper extremity	unknown	benign	0	0	6000	4000
2	ISIC_0052212	IP_2842074	female	50.0	lower extremity	nevus	benign	0	6	1872	1053
3	ISIC_0068279	IP_6890425	female	45.0	head/neck	unknown	benign	0	0	1872	1053
4	ISIC_0074268	IP_8723313	female	55.0	upper extremity	unknown	benign	0	11	6000	4000

+ Code + Markdown

Figure 5: Screenshot of the database

2.3.2 Data Cleaning and repairing

For the task of melanoma detection, data sourced from Kaggle underwent rigorous analysis focusing on image quality. Images with low pixel counts or blurred quality were excluded to eliminate low-quality data. Erroneous data points, such as outliers in age, were corrected by replacing them with average values to enhance accuracy. Furthermore, data standardization was carried out using the standard scalar process in Python, leveraging the Pandas library for normalization. These preprocessing steps were crucial to ensure the reliability and consistency of the dataset, essential for training and evaluating machine learning models in melanoma detection research.

2.3.3 Model Development

This study highlights the robust performance of the Deep Learning System (DLS) across various skin conditions through an extensive development and validation process. The DLS not only produces primary diagnoses but also provides differential diagnoses, marking a significant advancement in supporting clinical decision-making. Moreover, its ability to handle a varying number of input images and metadata variables demonstrates its flexibility and adaptability to a wide range of clinical scenarios. This versatile approach ensures that the system can effectively cater to diverse clinical needs, enhancing its practical utility in dermatological practice [12].

In this study, transfer learning has been employed to enhance melanoma classification accuracy. Transfer learning leverages pretrained models, such as Inception V3, initially trained on extensive datasets for solving similar tasks. By retraining the final layer of Inception V3 with the specific dataset, its previously learned features and patterns have been effectively utilized. Hence, optimizing performance without starting from scratch. The dataset is divided into training, validation, and testing sets, often in a 70-15-15 ratio. The model is then trained using transfer learning, initialized with pre-trained weights from the ImageNet dataset **Error! Reference source not found.**. This approach significantly reduces both training time and the computational resources needed [14].

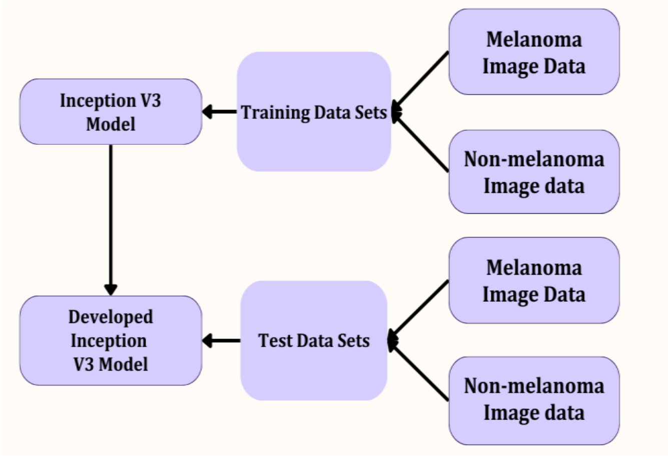

Figure 6: Model Development Diagram

Dataset of the current research has been partitioned into training and test sets, comprising 80% and 20% of the images, respectively. To argue with the dataset, techniques including shearing, zooming, flipping, and brightness adjustments have been applied, effectively doubling its original size. Inception has been fine-tuned V3 by adapting its final layer to the classification task, training the model over 6 epochs with a batch size of 32.

In addition to melanoma images, diverse non-melanoma skin diseases such as acne fulminans, acne nodules, eczema, Taksim, black spot, fungal acne, herpes, pityriasis versicolor, papule, pustular, rosacea, and whitehead have been incorporated **Error! Reference source not found.**. This approach has ensured the proposed model's robustness and ability to generalize across various skin conditions. The overall methodology underscores the commitment to leveraging advanced deep learning techniques for accurate and efficient melanoma detection in clinical settings. The overall process of training the Deep learning model is shown in Figure 6.

2.3.4 Implementation

This process includes importing necessary libraries, loading and preprocessing dataset, and creating and training the Inception V3 model in Jupyter Notebook. A Jupyter Notebook is an interactive tool for creating and sharing documents with live code, equations, visualizations, and narrative text. Popular in data science, research, and education, it combines code execution, data analysis, and explanations in one place. It's used for data science, statistical modeling, machine learning, and more **Error! Reference source not found.**. Additionally, the performance of the model is evaluated and visualized.

Importing Libraries and Loading the Dataset

The first step involves importing essential libraries and packages required for data manipulation, preprocessing, and model building. Key libraries include TensorFlow and Keras for deep learning, as well as Pandas and NumPy for data handling. The dataset, publicly available on Kaggle, contains melanoma records from the USA dated September 2018. Kaggle is an online platform that brings together data scientists, machine learning practitioners, and enthusiasts from around the world. It's a playground for exploring, learning, and competing in the exciting realm of data science[17].

Data Preprocessing

The dataset is loaded and described to understand its features. Data preprocessing involves handling missing values, data augmentation, and normalization to ensure the dataset is suitable for training the model using Pandas library.

Creating the Inception V3 Model

An instance of the Inception V3 model is created for image classification. The input images are resized to the specified IMAGE_SIZE with 3 color channels (RGB). The model is initialized with pre-trained weights from the ImageNet dataset. The top fully connected layers of the model are excluded to add custom layers for classification which will eventually enhance the overall performance of the designed system.

Model Compilation

The model is configured for training using the 'categorical crossentropy' loss function, 'adam' optimizer, and tracking the accuracy metric during training and validation.

Data Generators

Data generators are set up using ImageDataGenerator from TensorFlow/Keras to handle data augmentation and preprocessing. This includes rescaling pixel values and applying shear, zoom, and horizontal flip transformations.

Training the Model

The model is trained using the fit_generator method, which allows for efficient handling of large datasets by generating batches of data on the fly.

Evaluating and Visualizing Model Performance

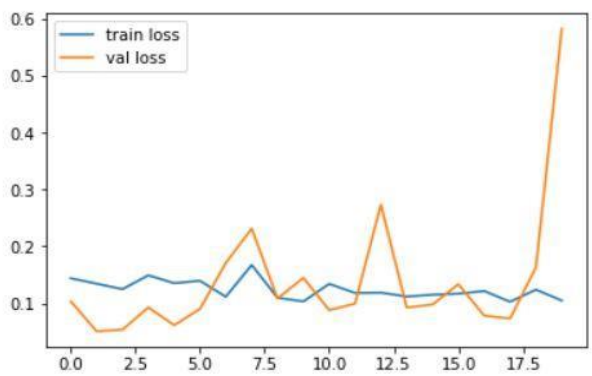

Figure 7: Plot Of the training loss (error) and validation loss across epochs

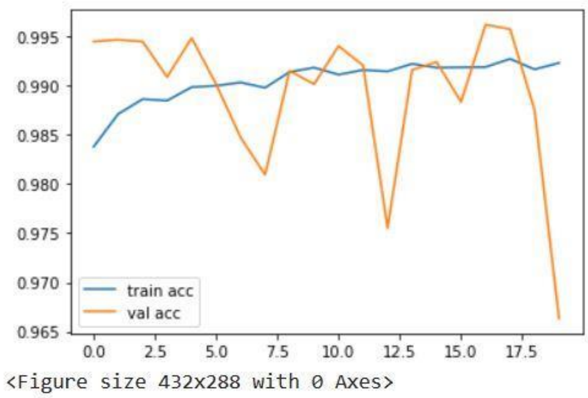

Figure 8: Plot of the training accuracy and validation accuracy across epochs

The training and validation loss, as well as accuracy over the training epochs, are plotted in Figure 7 and Figure 8 to visualize the model's performance. From the comparative analysis of these plots, it is ascertained that structured and iterative approach ensures a robust methodology for predicting melanoma using deep learning techniques, leveraging the power of the Inception V3 model for accurate and efficient classification.

3. System Testing and Result Analysis

Quality assurance (QA) ensures software systems meet specified requirements and behave as expected. It involves defining test parameters in the technical specification document and identifying defects during development to prevent post-release bugs [18]. In traditional software, QA focuses on verifying system functionality under various conditions. However, in machine learning, especially deep learning, the focus shifts to data quality, model performance, and system robustness. QA in ML involves validating and verifying both software artifacts and behavior, providing an objective assessment to understand and mitigate implementation risks. Comprehensive QA is crucial for reliable and accurate machine learning systems.

3.1 Testing

3.1.1 Unit Testing

Unit testing involves breaking down the program into individual units or components and testing each separately to ensure they perform as expected. Each unit, such as a function, method, procedure, module, or object, is isolated and verified for correctness. Key benefits of unit testing in model development include:

- Early Issue Detection: Identifies problems early in the development cycle.
- Isolation of Issues: Pinpoints specific components where issues arise.
- Code Refactoring Documentation: Provides a reliable foundation for making code improvements.

3.1.2 Integration Testing

Integration testing focuses on how different components or modules of the system interact and work together. In the context of this research work, integration testing ensures that the various steps—such as data pre-processing, Inception V3 model implementation, and result evaluation—function cohesively and correctly. Integration among every section of the program reduces the errors and elevates the performance of the system.

3.1.3 System Testing

System testing verifies the functionality and performance of the entire system as a whole. This involves testing the complete data processing pipeline, model training, prediction, and result evaluation to ensure the model operates as intended [19].

3.1.4 Performance Testing

Performance testing evaluates the model's efficiency, speed, and resource consumption. This ensures that the model performs well even with large datasets and can deliver results within acceptable time frames.

3.1.5 Security Testing

Security testing addresses potential vulnerabilities or risks in the model's implementation, particularly when handling sensitive medical data. This ensures that the system is secure and protects patient information.

These comprehensive testing approaches ensure that the machine learning system is robust, reliable, and meets all specified requirements.

3.2 Result Analysis:

The developed model in this research work achieves an average accuracy of 99.01% with the experimental values used for training. While this accuracy is sufficient for implementation on the website, there is potential for further improvement. Increasing the dataset size and the number of training epochs could enhance the model's performance.

This figure demonstrates a positive detection from the testing data, validating the model's accuracy.

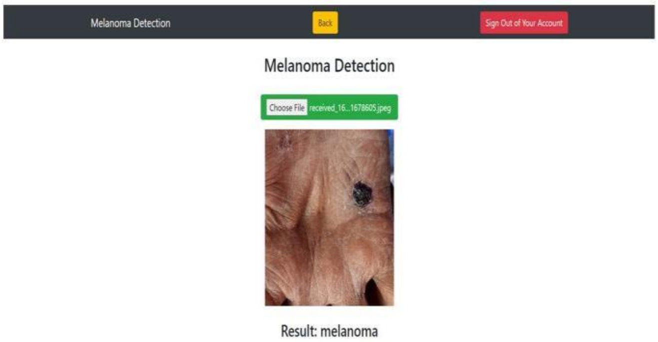

Figure 9: Analysis Result on webpage

In recent years, significant research efforts have been directed towards improving the diagnosis of melanoma skin diseases. These advancements have led to the development of more accurate and reliable diagnostic models, contributing to better clinical outcomes.

Table -1: Sample Table format

Epoch	Train loss	Train Accuracy	Value loss	Value Accuracy
1	0.1873	0.9785	0.1033	0.9945
4	0.1270	0.9889	0.0927	0.9909
8	0.1604	0.9898	0.2312	0.9809
12	0.0932	0.9932	0.0993	0.9921
16	0.1255	0.9922	0.1333	0.9883
20	0.1042	0.9923	0.5821	0.9663

A comprehensive array of testing methodologies has been meticulously applied to rigorously evaluate the efficacy, robustness, and reliability of carefully crafted deep learning model. This pivotal phase of the development process is instrumental in validating the model's performance across various dimensions, ensuring it meets the highest standards of accuracy and generalization.

5. DISCUSSION

The proposed model achieves an impressive average accuracy of 99.01% with the experimental values used for training. While this level of accuracy is sufficient for implementation on the website, there is potential for further improvement. Increasing the dataset size and the number of training epochs can enhance the model's performance further, allowing for even greater precision and reliability.

In recent years, significant research efforts have been directed towards improving the diagnosis of melanoma skin diseases. These advancements have led to the development of more accurate and reliable diagnostic models, contributing to better clinical outcomes. The integration of cutting-edge machine learning techniques has played a pivotal role in these improvements, enabling the detection and classification of melanoma with higher accuracy.

A comprehensive array of testing methodologies has been meticulously applied to rigorously evaluate the efficacy, robustness, and reliability of our carefully crafted deep learning model. This pivotal phase of the development process is instrumental in validating the model's performance across various dimensions. Ensuring that the proposed model meets the highest standards of accuracy and generalization is crucial for its successful deployment in clinical settings. By rigorously testing and validating the model, its ability to perform reliably in real-world applications, ultimately contributing to better patient outcomes and advancing the field of melanoma diagnosis has been acknowledged.

6. CONCLUSIONS

The newly developed model demonstrates a commendable accuracy of 99.01% despite being trained on a relatively limited dataset. This research employed a deep convolutional neural network, specifically Inception v3, to classify melanoma and other skin diseases. The user-friendly website interface allows patients to identify melanoma with just a few clicks.

The outcomes of this research show proper utilization of very deep convolutional neural networks, combined with transfer learning and fine-tuning on dermoscopic images, achieve better diagnostic accuracy compared to the existing technologies used by expert doctors and clinicians. Unlike other studies, this paper introduces a new method for melanoma detection using a variety of skin disease tests and non-melanoma datasets. This approach significantly enhanced the accuracy of the applied AI algorithm, Inception v3.

The website offers people across the globe the opportunity to detect early signs of melanoma and take preventive measures. Dermatologists in the country will benefit from this tool and can use it to aid in patient treatment.

Looking ahead, the dataset can be expanded to further improve the model's accuracy, particularly for non-melanoma skin types. Additionally, this model can be integrated seamlessly with the website, which still requires further enhancements on both the front-end and back-end.

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