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An Effective Approach to Detect Skin Cancer Using Deep Learning

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Abstract- The medical industry is advancing with the innovation of new technologies; newer healthcare technology and treatment procedures are being developed. Biotechnology is the base for all these advancement in technology. With the advent of several pollutants, cosmetics and chemicals into our day to day lives, the health of individuals has been deteriorating every day. These not only effects physical or mental health, but also change our lifestyles. This project work concentrates on identification of skin cancer, caused by one of the above-mentioned conditions. The images are processed using combinations of Deep learning and image processing to detect the stage of cancer. Images of the affected area are captured with the help of derma scope. Several algorithms have been proposed to detect skin cancer but most of the inputs are fed manually. The main objective of this project is to develop a Deep learning algorithm which requires minimal intervention of human. The tool we have used for the detection of cancer cells is Jupyter Notebook. At last DL classifier is used to classify.

In our project we have used algorithms like ResNet 50 as proposed and Artificial Neural Network (ANN) as existing. All are measured in terms of accuracy and from the results the proposed Artificial Neural Network (ANN) performs well compared to other algorithms.

Keywords- Skin Cancer Detection, Deep Learning, Image Processing, ResNet-50, Artificial Neural Network (ANN), Jupyter Notebook, Derma Scope, Medical Imaging, Cancer Classification, Healthcare Technology.

I INTRODUCTION

The revolution of computer in the past decades, have unfolded the use of computers, be it any field. The Era of maintaining huge records for data storage has evolved. Computers have become most used tool in almost each field.

It has made the life of humans easier. Also, Computers have made research very easier. Biomedical has offered modern medical devices for diagnostic and preventive purposes, which include diagnostic test kits, vaccines, antibodies and radio-labelled biological therapeutics used for imaging and investigation purpose. It has played a prominent role in improving the challenges regarding to human health as it has flexibility to reduce global health differences by the provision of promising technologies. Many types of cancers are being detected and has become very common disease with the evolution of the technology. Skin cancer is the most explored disease. With increased use of cosmetics, pollution & radiations, cancer is becoming a common disease in the modern era. The images of the affected area termed as ―lesion‖ are captured with the help of derma scope and are fed as input to the algorithm. Several algorithms have been proposed which requires input to be fed manually. The aim of this work is to propose an algorithm which requires minimal intervention of doctors. In the recent years, due to the increased use of cosmetics, and pollution & radiations, cancer is becoming a common disease in the modern era.

Stages of skin cancer As soon as the disease is discovered, next task would be determining in which stage the cancer is. The stage in which the cancer is can be determined by various factors such as thickness, the depth of penetration, and the extent to which the melanoma has spread. Based on the stage determined, the patients are treated. The first stage of the skin cancer, that is the early stage of melanoma (Stage 0 and Stage 1) are insular. Stage 0 tumours are in situ, which means they are non-invasive and have not entered beneath the external layer of the skin (the epidermis).

Stage I tumours have attacked beneath the epidermis into the skin's next layer (the dermis) yet are little and have no different characteristics, for example, ulceration that put them at high danger of spreading (metastasizing) to close- by lymph hubs or beyond.

Stage II tumours, however limited, are bigger (for the most part 1 mm. thick or bigger) and additionally may have different characteristics, for example, ulceration that put them at high danger of spreading to the close- by lymph hubs or beyond. They are viewed as transitional or "high-chance" melanomas. Further developed melanomas (Stages III and IV) have metastasized to different parts of the body. There are additionally subdivisions inside stages.

II EXISTING SYSTEM

A Artificial Neural Network (ANN) is a class of neural networks where connections between nodes form a graph along a temporal sequence. This allows it to exhibit temporal dynamic behavior. Derived from feed forward neural networks, ANNs can use their internal state (memory) to process variable length sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition or speech recognition.

The term "recurrent neural network" is used indiscriminately to refer to two broad classes of networks with a similar general structure, where one is finite impulse and the other is infinite impulse. Both classes of networks exhibit temporal dynamic behavior. A finite impulse recurrent network is a directed acyclic graph that can be unrolled and replaced with a strictly feed forward neural network, while an infinite impulse recurrent network is a directed cyclic graph that can not be unrolled.

Both finite impulse and infinite impulse recurrent networks can have additional stored states, and the storage can be under direct control by the neural network. The storage can also be replaced by another network or graph, if that incorporates time delays or has feedback loops. Such controlled states are referred to as gated state or gated memory, and are part of memory networks (LSTMs) and gated recurrent units. This is also called Feedback Neural Network (FNN).

III PROPOSED WORK

A residual neural network (ResNet) is a type of artificial neural network (ANN) that builds upon constructs inspired by pyramidal cells in the cerebral cortex. ResNet achieves this by incorporating skip connections, or shortcuts, that allow the network to bypass one or more layers. These skip connections address common challenges in deep learning, particularly the vanishing gradient problem and the degradation (accuracy saturation) problem. By skipping layers, ResNet ensures that the learning process remains stable even as the network depth increases.

ResNet models typically utilize double- or triple-layer skips containing non-linear activation functions, such as ReLU (Rectified Linear Unit), and batch normalization layers in between. This design prevents information loss and ensures effective gradient propagation. In some cases, an additional weight matrix may be introduced to learn the skip weights dynamically, forming what are known as HighwayNets. Furthermore, architectures that incorporate multiple parallel skip connections are categorized as DenseNets, which leverage feature reuse to enhance learning efficiency.

The inclusion of skip connections serves two primary purposes. Firstly, it prevents vanishing gradients by maintaining gradient flow during backpropagation, ensuring that deeper layers continue to receive meaningful updates. Secondly, it mitigates the degradation problem, where increasing the network depth can paradoxically result in higher training error. This occurs because, without proper optimization, deeper networks struggle to effectively learn from data. By enabling direct pathways for gradient flow, ResNet models circumvent these issues and maintain stable learning dynamics.

During training, the network adapts by tuning the weights of the skip connections. Initially, it suppresses the upstream layer while amplifying the previously skipped layer, facilitating efficient gradient flow. In simpler scenarios, only the weights associated with the adjacent layer's connection are updated, without explicitly learning the skipped connection's weights. However, in cases where intermediate layers involve non-linear transformations, an explicit weight matrix is required to optimize the skip pathways effectively.

By integrating skip connections, ResNet simplifies the training process by temporarily reducing network complexity. This approach accelerates early-stage learning by minimizing the impact of vanishing gradients, as fewer layers need to be traversed during backpropagation. As training progresses, the network gradually incorporates the skipped layers, refining its feature extraction capabilities. Toward the later stages of training, when all layers become fully active, the network aligns more closely with the feature space, facilitating faster and more stable convergence.

In contrast, non-residual networks lack this structured optimization process, making them more susceptible to disturbances that push them away from the learned feature manifold. Consequently, such networks often require larger datasets and extensive training to recover from these deviations. By leveraging residual learning, ResNet architectures strike a balance between network depth and stability, making them highly effective for deep learning tasks, including image classification, object detection, and segmentation

IV COMPARATIVE STUDY OF EXISTING AND PROPOSED SYSTEM

This project presents recent advancements in using computer vision-based systems for the classification of liver varieties. With the increasing integration of artificial intelligence in medical imaging, automated classification techniques have become essential for improving diagnostic precision and reducing human intervention. A computer-vision application using image processing techniques typically involves five fundamental stages: image acquisition, pre-processing, segmentation, object detection, and classification. Each of these steps ensures that the raw input data is refined, features are effectively extracted, and the classification process achieves maximum accuracy.

This survey highlights various approaches employed in liver grading practices and summarizes their relevance in medical diagnostics. The primary objective of this study is to conduct a comparative analysis of different classification models to identify the most efficient technique for liver classification tasks.

In our project, we will be utilizing Artificial Neural Networks (ANN) as the existing system and ResNet-50 as the proposed system. ANN, while effective in many classification tasks, faces limitations in handling large-scale image data due to its shallow architecture, which restricts feature extraction capabilities. On the other hand, ResNet-50, a deep convolutional neural network (CNN), is designed to address such challenges by incorporating residual learning techniques, which allow deeper network training without degradation. This enables ResNet-50 to capture intricate patterns and textures in liver images more effectively than ANN.

The accuracy of both models will be calculated and compared based on various performance metrics such as precision, recall, F1-score, and overall classification accuracy. From the results, it is evident that ResNet-50 outperforms ANN in terms of accuracy, demonstrating its effectiveness in medical imaging tasks. The findings of this study highlight the importance of advanced deep learning models in enhancing automated liver classification, ultimately aiding healthcare professionals in more precise and efficient disease diagnosis.

This comparative study reinforces the potential of deep learning in medical applications and paves the way for future research in developing even more robust and efficient classification techniques for liver disease detection.

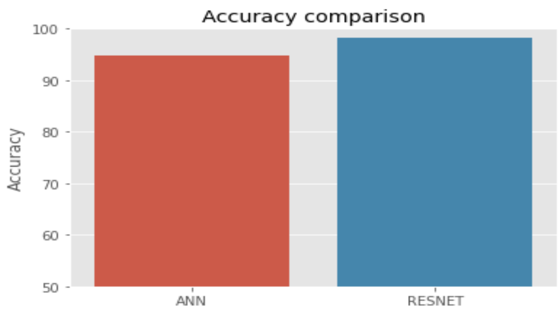

Fig 1 Accuracy comparison

V METHODOLGY

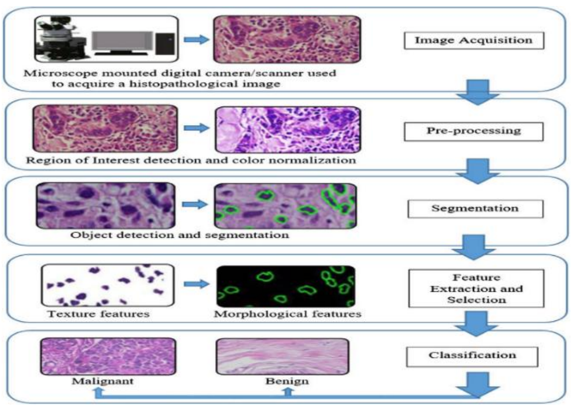

Fig ii Module Classification

1. Image Acquisition Image

Acquisition is the process of collection of images. These images are downloaded from the online dataset provider called Kaggle.com.

2. Image Preprocessing

Image preprocessing includes converting normal images into resize images. Grayscale images have the combination of black and white. Grayscale images help to reduce noise and also make the background neutral. It also helps to improve brightness of the image. Data augmentation is a way of creating new data which has benefits like the ability to generate more data from limited data and it prevents over fitting.

3. Image Segmentation

Image segmentation breaks the image down into meaningful regions. It divides digital image into multiple segments. The goal is to simplify or change the representation into more meaningful image. It differentiates between the objects we want to inspect further and the other objects or their background. It consists of segmenting the converted grayscale images using K means segmentation.

4. Feature Extraction

Feature extraction is extracting or showing of the segmented portion of the image so that classification becomes easy. Features are extracted in order to differentiate between the images. Features extraction is used in almost all Deep vision algorithms. The common goal of feature extraction and representation techniques is to convert the segmented objects into representations that better describe their main features and attributes.

5. Classification

Here we use the concept of Classifiers and its architecture for classification method. The last module includes the classification in which Tensor Flow and Deep Learning algorithm will be used. Tensor Flow is a python-friendly open source library for numerical computation that makes Deep learning faster and easier. Tensor Flow allows developers to create dataflow graphs - structures that describe how data moves through a graph, or a series of processing nodes. Each node in the graph represents a mathematical operation, and each connection or edge between nodes is a multidimensional data array, or tensor.

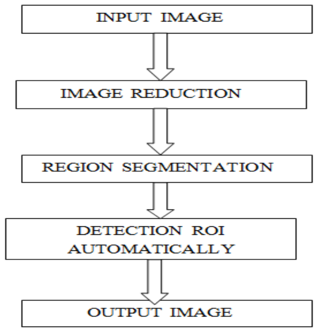

Fig iii Flow Diagram

VI RESULT AND ANALYSIS

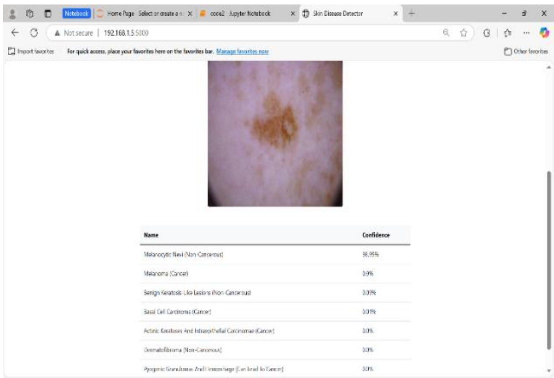

Fig iv Non Cancerous Result

The given image displays the results of a skin disease detection system utilizing the ResNet algorithm. According to the model's classification, the lesion in the image has been identified as Melanocytic Nevi (Non-Cancerous) with a 98.99% confidence score. This suggests that the detected skin condition is most likely benign, meaning it is not associated with cancer.

Other possible conditions, such as Melanoma (0.9%), Benign Keratosis-Like Lesions (0.09%), and Basal Cell Carcinoma (0.01%), were considered but assigned significantly lower probabilities, making them much less likely.Fig 7

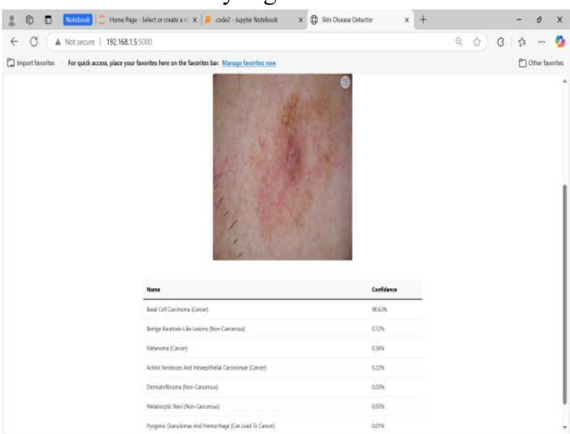

Fig v Cancer result

The results displayed in the image are derived from a skin disease classification model based on the ResNet algorithm, a deep learning convolutional neural network (CNN) architecture known for its strong feature extraction capabilities. The model has classified the given skin lesion with a high confidence of 98.63% as Basal Cell Carcinoma (BCC), a common type of skin cancer. Other potential conditions, such as benign keratosis-like lesions (0.72%) and melanoma (0.36%), have been assigned much lower probabilities, indicating that the model is fairly certain about its primary classification.

VII CONCLUSION

This project demonstrates the modeling of skin cancer as a classification task and describes the implementation of a deep learning (DL) approach for classifying skin cancer into benign or malignant categories. The study emphasizes the growing significance of AI-driven methodologies in medical diagnosis, particularly in dermatology, where early and accurate detection is crucial for effective treatment. The deep learning model was trained using a large dataset of skin lesion images, leveraging advanced image processing techniques to improve classification accuracy.

The performance of the deep learning-based model was evaluated and compared with the existing classification system. The comparison was conducted based on several performance metrics, including accuracy, precision, recall, and F1-score. It was observed that the deep learning approach demonstrated superior classification performance compared to traditional machine learning or rule-based algorithms. This improvement is attributed to the ability of deep learning models to extract complex hierarchical features from images, enabling a more robust and precise differentiation between benign and malignant lesions.

Furthermore, the use of convolutional neural networks (CNNs) in skin cancer detection has proven to be highly effective, as CNNs can capture intricate patterns in dermoscopic images that might be challenging for traditional methods. The proposed deep learning model not only enhances classification accuracy but also minimizes false positives and false negatives, thereby improving the reliability of automated skin cancer detection systems.

Based on the results obtained in this study, machine learning (ML) and deep learning techniques are more efficient and reliable compared to conventional classification methods in skin cancer detection. The success of this approach highlights the potential for AI-driven diagnostic tools to assist dermatologists in early detection, ultimately leading to improved patient outcomes. Future work can focus on optimizing the model further by incorporating more diverse datasets, refining pre-processing techniques, and exploring hybrid models that integrate multiple deep learning architectures for even higher accuracy and generalizability.

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