Employing Convolutional Neural Networks for the Early Identification of Skin Cancer

Abhishek Raj Mishra[1], Shivraj Kumar Chettri[2], Sakshi Kumari[3], Jeeva Selvaraj[4]

[1] *Department of Information Science and Engineering Jain Deemed-To-Be University, Kanakpura Road, Jakkasandra, 562112, INDIA*

[2] *Department of Information Science and Engineering Jain Deemed-To-Be University, Kanakpura Road, Jakkasandra, 562112, INDIA*

[3] *Department of Information Science and Engineering Jain Deemed-To-Be University, Kanakpura Road, Jakkasandra, 562112, INDIA*

[4] *Department of Information Science and Engineering Jain Deemed-To-Be University, Kanakpura Road, Jakkasandra, 562112, INDIA*

Abstract. Preventing skin cancer, particularly melanoma, is crucial for reducing mortality rates and improving patient prognosis. This study proposes a comprehensive approach that utilises convolutional neural networks (CNNs) to further improve the accuracy and diagnosis of skin cancer. Our methodology involves developing and improving a sophisticated deep learning model by utilising an extensive collection of dermatological images that cover a wide range of skin types and stages of malignancy. The CNN model effectively distinguishes between benign and malignant tumors due to its capacity to collect and comprehend intricate information from these pictures. We emphasise the power of early treatment of cancer and strive to reduce the occurrence of false negatives, a common issue associated with traditional diagnostic methods. Our approach streamlines the integration of this state-of-the-art technology into clinical practice by offering dermatologists a user-friendly interface. An extensive assessment of the system's effectiveness, based on current diagnostic criteria, shown a significant improvement in the rates of early detection. This work not only demonstrates the potential of CNNs in medical imaging, but also paves the way for their application in cancer and dermatology, ultimately leading to enhanced patient outcomes.

Keywords: *Skin Cancer, CNN, Machine Learning.*

1. INTRODUCTION

Globally, skin is known as the world's most deadliest cancer type, with its incidence showing a marked increase in recent years. The World Health Organisation (WHO) [2] documented over 5.3 million cases of skin cancer in 2020, representing about 5% of all cancer diagnoses that year. Despite differing opinions, researchers, including Melina Arnold and colleagues (2022), anticipate a decline in both mortality and new cases of skin cancer [1]. However, fewer Projections for 2040 suggest around 96,000 deaths and 510,000 new cases, a noticeable change from the 325,000 cases in 2020[5]. Research by the American Cancer Society highlights multiple factors driving the rise in cancer rates, particularly skin cancer. Key among these is heightened vulnerability to the sun's ultraviolet (UV) radiation, a known carcinogenic factor. Prolonged UV exposure can harm skin cell DNA, potentially triggering skin cancer. Other risk elements include genetic predisposition, sunburn history, and physical traits like fair skin, blue eyes, or red hair. The WHO identifies Basal cell carcinoma (BCC) as the most common skin cancer variant, Constituting more than 75% of all instances of skin cancer [3]. Although BCC while often exhibiting sluggish growth and infrequent metastasis, if not treated, it can lead to notable deformity. Squamous cell carcinoma (SCC), another form, makes up about 20% of skin cancers. SCC [4] often grows slowly but can metastasize if not promptly treated. Melanoma, a more dangerous skin cancer type, accounts for 1% of cases but most skin cancer-related deaths. Due to its aggressive metastatic nature, early detection and treatment of melanoma, which can spread to various body parts, are crucial.

1.1 Motivation

In many instances, convolutional neural networks (CNNs) surpass conventional machine learning techniques as a potent tool for image-based categorization tasks. They are particularly useful for tasks like object recognition, scene categorization, and medical image analysis because of their capacity to extract hierarchical features and capture local spatial correlations from images. Convolutional Neural Networks (CNNs) are particularly useful for image-based categorization, their inherent capacity to programmatically extract hierarchical attributes from unprocessed pixel input have allowed many novel Research achievements. CNNs can automatically extract pertinent features at various levels of abstraction, from basic edges and textures to more intricate patterns and structures, thanks to the hierarchical feature learning technique. Because of their innate ability to learn hierarchical representations, CNNs are excellent at tasks involving images because they can distinguish between high-level and low-level meanings, which helps them perform better in picture classification than more conventional techniques. Here are some of the reasons why CNNs are better for image-based classification:

— Local Spatial Dependencies: CNNs explicitly consider local spatial relationships between pixels, allowing them to identify patterns and features that are relevant for image classification. Unlike traditional machine learning algorithms that treat images as flat arrays of pixels, CNNs utilize convolutional layers to extract local features and build progressively more complex representations.

— Hierarchical Feature Extraction: CNNs employ a hierarchical architecture that captures features at different levels of abstraction. This hierarchical structure mimics the human visual system's ability to detect edges, lines, shapes, and objects at progressively finer scales. By extracting features at various levels, CNNs can effectively represent complex visual information.

— Parameter Sharing: CNNs employ parameter sharing, where a set of weights is applied to multiple locations the input provided image. This Considerably reduces the quantity of parameters being compared to traditional CNNs are created by connecting all nodes in a network less prone to overfitting and more efficient to train.

— Translation Invariance: CNNs are inherently translation invariant, meaning that the location of an object in an image does not affect its classification. This property is crucial for image-based classification tasks, as objects can appear in different positions within an image.

— Robustness to Noise: CNNs are relatively robust to noise and variations in illumination, making them suitable for real-world applications where images may not be perfectly clear or consistent.

The CNN Algorithm has repeatedly shown that it is capable of being more than just a straightforward algorithm built on fundamental machine learning concepts. It can produce some quite complicated answers for a wide range of difficult issues. According to the Journal article "Going Deeper With Convolutions"[6], they were able to develop the inception module using the CNN that was already in place. According to the researchers, the Inception module functions as a revolutionary convolutional neural network (CNN) architecture that enables the creation of bigger, deeper networks at a reduced computing cost. Parallel branches of various convolutions and pooling processes make up the inception module. These branches are concatenated into a single output. The study demonstrates how CNNs' performance on a range of computer vision tasks, including face recognition, object identification, and image classification, can be enhanced by the inception module. Additionally, GoogLeNet, a 22-layer CNN that employs the inception module and produces cutting-edge outcomes on the ImageNet task, is presented in the study.

The development of ResNet (Rest Network) is one of Pioneer's accomplishments. ResNet is a kind of convolutional neural network (CNN) that circumvents the issue of vanishing or bursting gradients by learning identity mappings using residual blocks. He et al. submitted ResNet in 2015[7], and it was the winner of the ImageNet challenge that same year. Motivated by the impressive progress made with CNNs and the flexibility they provide in building complex algorithm designs, we have chosen to use CNNs as the foundation of our main algorithm.

1.2 Objectives

The principal of this study is to design, implement, and evaluate a Convolutional Neural Network (CNN) model and its counterparts for the early diagnosis of skin cancer. The overarching goal is to leverage the capabilities of CNNs in image analysis to enhance the accuracy and the efficacy of early identification of skin cancer.

— **Early Detection Emphasis**: The foremost goal is to focus on the timely identification of skin cancer lesions. Early identification of malignancies significantly improves the likelihood of a successful therapy is increased, hence minimising the risk of serious health complications. By developing a CNN model, we aim to create a robust system that can identify subtle signs of skin cancer in medical images, enabling prompt intervention.

— **Utilizing Image-Based Information**: The research aims to harness the power of CNNs in processing and understanding visual data. Skin cancer often presents visually identifiable patterns and characteristics that can be captured through image analysis. The CNN model will be designed to automatically learn and extract relevant features from dermatological images, allowing for more accurate and objective diagnosis compared to traditional methods.

— **Improving Diagnostic Accuracy**: The research strives to contribute to the enhancement of likelihood ratio in cancer detection. By using the profound ability of CNNs to learn hierarchical representations, the model aims to discern intricate patterns indicative of both malignant and benign skin conditions. The ultimate goal is to reduce false positives and negatives, providing medical practitioners with a more reliable tool for early diagnosis.

— **Incorporating Diverse Data Sources**: The research will explore the inclusion of diverse datasets, encompassing a wide range of skin types, ages, and ethnicities. This ensures the generalizability of the developed CNN model across different populations. By incorporating a comprehensive dataset, the goal is to create a more inclusive and robust predictive model that performs effectively across various demographic groups.

2. LITERATURE REVIEW

2.1 Overview of Skin Cancer

UV radiation exposure is intimately associated with Skin cancer, the prevailing form of cancer on a global scale. Skin cells are the source of skin cancer. Although melanoma is less prevalent, it is more aggressive, BCC and SCC are prevalent and may present as growths or lesions[2]. Fair skin, lots of moles, family history, UV radiation, and a unhealthy immune system are risk factors. Sunscreen and routine skin examinations are two aspects of prevention. Surgery, radiation, immunotherapy, and chemotherapy are among the treatments that are informed by the diagnosis, which is usually made through biopsy. As the prevalence of this mostly avoidable malignancy rises worldwide, public health efforts emphasize sun safety and early identification as critical components of effective care. A tumor's size, its penetration into surrounding tissues, and whether it has metastasized—or spread—to other regions of the body are all taken into account when staging skin cancer. TNM is an acronym that represents the three key factors used to assess cancer: tumour, node, and metastasis. and The staging categorization for skin cancer described is the most often utilised. A summary is provided below:

— **Stage 0 (In Situ):** Cancer is at its initial stage, characterized by the presence of aberrant cells solely in the epidermis, without any invasion into deeper tissues.

— **Stage I:** The tumor is characterized by its modest size, limited presence, and absence of dissemination to adjacent lymph nodes or other body regions. It is usually limited to the skin.

— **Stage II** denotes that the tumor has grown in size or has infiltrated adjacent tissues, but there is no evidence of metastasis to lymph nodes or distant organs.

— **Stage III:** The staging categorization for skin cancer is frequently used. The malignancy has spread to nearby lymph nodes., indicating a higher level of advancement. The original tumor might vary in size.

— **Stage IV (Terminal Stage):** This represents the most complex phase, described by the metastasis of cancer to later organs or lymph nodes situated at a considerable distance from the primary tumour. The evaluation of the main tumor's dimensions and its metastasis to lymph nodes or distant organs is taken into account**.** However, most people fail to recognize the basic visual differences of stages within Skin Cancer which can be broken down into two: Benign and Malignant.

Benign refers to something, like a benign tumor, that does not fundamentally pose a risk to one's health. The term "benign" in medical terminology refers to lumps or tumors that are not malignant. A benign tumor stays in one place in the body and does not spread. When a tumor spreads to nearby tissues or distant bodily parts, it is no longer benign and is instead considered malignant or cancerous[8].

Here's a concise overview of visible benign skin cancer skin tissues shown in Fig 1:

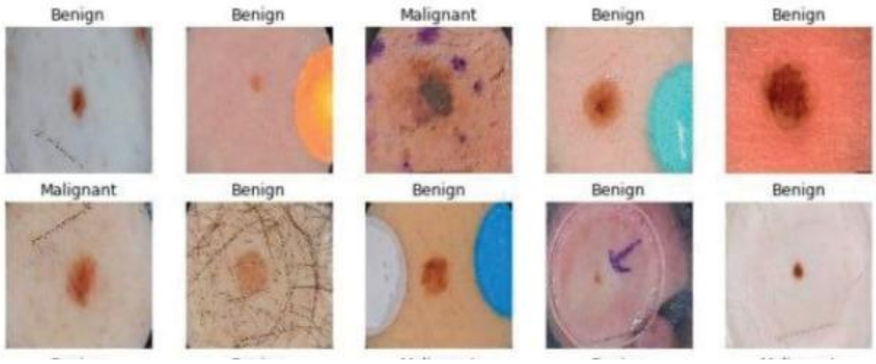

Fig. 1. Benign Skin Cancer Visible on Skin Tissues

In some cases, it may be possible to observe certain visual clues that raise suspicion about whether a skin lesion is benign or malignant, but visual examination alone is not definitive. Both benign and malignant skin lesions can display a wide range of appearances, and various factors contribute to the visual assessment. Below given image can you give a basic understanding of how cell grows and deforms itself into something bigger when it becomes malignant and cancerous[8] depicted in Fig 2.

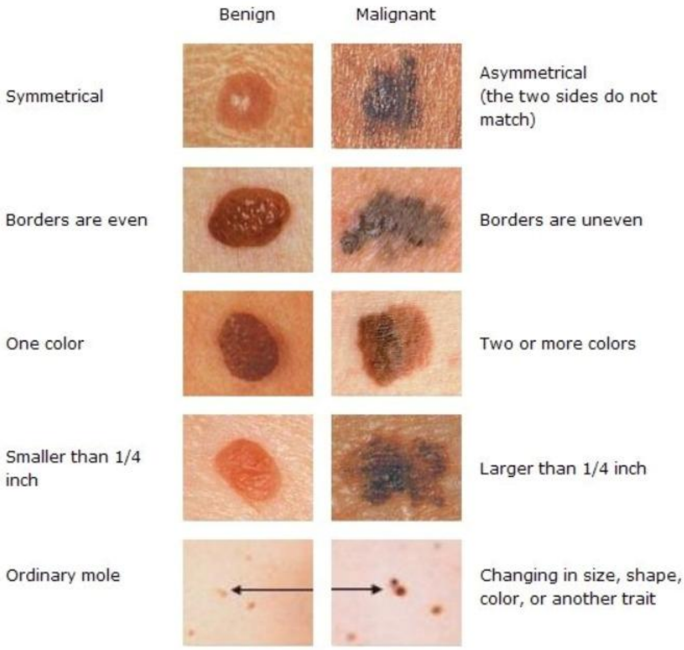

Fig. 2. Visual Difference between Benign and Malignant Skin Cancer Tissues

2.2 Current Method of Diagnosis

The current approach to diagnosing skin cancer is a multi-step process that includes visual inspection, dermoscopy, and biopsy, following a series of trial and error attempts.

— **Visual examination**: Visual examination[9] is the first stage in the diagnosis of skin cancer, during which a dermatologist meticulously inspects the patient's skin for any questionable abnormalities. This means doing a comprehensive examination of the skin from head to toe, paying special attention to regions like the face, ears, neck, and hands that are frequently exposed to sunlight. During visual examination, dermatologists search for distinct attributes that could suggest the existence of skin cancer, including:

- Asymmetry: The lesion exhibits dissimilarities between its two halves.
- Border: The lesion exhibits an asymmetrical, jagged, or indistinct border.
- Color: The lesion exhibits polychromaticity or irregular distribution of colors.
- Diameter: The lesion exceeds 6 millimeters (about the dimensions of a pencil).
- Progressing: The lesion is undergoing changes in size, form, or colour over time.

— **Dermoscopy**: It is often referred to as chemiluminescence microscopy, is a non-invasive method that use a specialized handheld microscope with polarised light to thoroughly analyze skin diseases. This approach enables dermatologists to perceive structures that are imperceptible to the unaided eye, such as the organization of pigment and blood arteries within the lesion. Through the examination of these structures using dermoscopy, dermatologists can acquire vital knowledge about the characteristics of the lesion and make more educated judgements regarding the need for a biopsy. Dermoscopy has demonstrated a notable enhancement in the precision of skin cancer identification, especially during the first phases when distinguishing between malignant and non-malignant diseases can be challenging. Research has demonstrated that digital dermoscopy can attain comparable or even superior diagnostic precision in comparison to traditional dermoscopy. A 2018[9] meta-analysis of over 30 trials found that digital dermoscopy was comparable to traditional dermoscopy in terms of accuracy, with a level of sensitivity of 91% and a specificity of 88% in identifying melanoma.

— **Biopsy**: A biopsy is the sole conclusive technique for diagnosing skin cancer. The procedure entails extracting a small portion of the lesion, either via a punch biopsy or an excisional biopsy. Subsequently, the sample is forwarded to a pathologist for a meticulous analysis under a microscope in order to ascertain the presence of malignant cells.

There are two primary categories of biopsies commonly employed for the diagnosis of skin cancer:

1. A punch biopsy is a procedure in which a tiny, round slice of skin is taken using a specialized instrument known as a punch biopsy tool. This form of biopsy is appropriate for tiny lesions.

2. An excisional biopsy involves the complete removal of the lesion, including a portion of healthy skin surrounding it. This particular biopsy method is recommended for bigger lesions or those that exhibit worrisome characteristics. Once the biopsy sample is examined under a microscope, the pathologist will look for specific cellular changes that indicate skin cancer. These changes may include:

- Abnormal growth patterns of cells
- Loss of normal cell architecture
- Presence of atypical cells

If cancerous cells are found, the pathologist will determine the type and stage of skin cancer, which is crucial for guiding treatment decisions.

2.3 Previous Work on Skin Cancer Detection using Machine Learning

Several significant advancements have been made in developing algorithms for differentiating between cancerous and non-cancerous tissues. One notable example is the method proposed in the Examine the technique of classifying Dermoscopic Images by utilising a combination of Convolutional Neural Networks that have been fine-tuned.[10] This method classifies skin lesions in dermoscopic images using a combination of three pre-trained models available: Xception, ResNet50, and Vgg-16.. These models are adapted for the ISIC 2016 dataset by modifying their fully connected layers. The outputs from these models are merged using a WFS. From the research of scientists at Korea[13], we found out that the use of other models like VGG and DenseNet helps in better understanding of how skin lesions show a different pattern of growth every time. This became a significant reason for us to start collecting a larger set of data for training and testing as this would help us in better diagnosis of the skin cancer.

The researchers assert that their method surpasses existing ones in terms of performance and accuracy, potentially aiding in melanoma diagnosis.[11] Another group of researchers introduced DermoExpert, an automated system that integrates the dermoscopic pictures are classified into multiple divisions of skin lesions using a complex CNN after pre-processing. Additionally, a comprehensive study reported by Science Digest[12] delves into the application of CNNs for skin cancer classification. This study involves a detailed review of literature and collaboration with numerous authors and organizations, such as the "Digital Age Biomarkers for Oncology Group" and the Germany-based Cancer Consortium. It examines 19 studies, with 11 focusing on dermoscopic image classification, 6 on clinical image classification, and 2 on dermatopathological studies using digitized histopathological slides. The findings from these studies consistently show that CNN-based classifiers either match or exceed the accuracy of human experts in classifying skin cancer. This review highlights the potential of CNNs in creating digital biomarkers that are clinically significant in dermatology and dermatopathology, stressing the need for diverse and representative test sets in Further investigation.

In the exploration of noninvasive features for cancer diagnosis, the research paper[14] delves into the efficacy of various deep learning methods. “Artificial Neural Networks (ANNs)” are employed for their predictive and classificatory prowess, harnessing learned patterns to forecast outcomes. “Convolutional Neural Networks (CNNs)” are particularly lauded for their superior image classification capabilities, making them indispensable in the analysis of medical imagery. “Kohonen Self-Organizing Neural Networks (KNNs)” are adept at mapping intricate, high-dimensional data relationships while preserving the input space's topological features. Lastly, “Radial Basis Function Neural Networks (RBFNs)” are utilized for their exceptional function approximation and pattern recognition abilities, crucial for differentiating between various skin lesion types. These models are strategically chosen for their unique strengths in processing medical images, which include essential tasks such as feature extraction, pattern recognition, and classification, thereby enhancing the accuracy of skin cancer diagnoses.

Our other research paper presents[15] an innovative approach to skin cancer detection by harnessing the power of deep learning techniques. At the heart of the study is the application of a convolutional neural network to the publicly found ISIC-2018 dataset, which comprises a diverse array of skin cancer lesion images. The process is meticulous, involving the enhancement of image quality through model ESRGAN and careful pre-processing that includes division, normalization, and scaling. Additionally, the study incorporates multiple cnn models, which are fine-tuned to accelerate performance. The results are promising, with the CNN achieving an accuracy rate of 72.2%, and the transfer learning models showing even higher efficacy, particularly Iv3, which tops the accuracy chart at 75.5%. The paper underscores the power of using ESRGAN in preprocessing to bolster image clarity, significantly contributing to the models’ high accuracy rates. The conclusion drawn is that this deep learning approach could substantially aid dermatologists in diagnosing skin cancer, thereby potentially reducing their workload.

3. METHODOLOGY

3.1 Collection Data

Datasets are abecedarian in training convolutional neural networks (CNNs) and other machine learning algorithms, as they supply the critical training data necessary for these models to fete and learn patterns. inadequate data can lead to ineffective literacy and poor model conception. This discussion focuses on two specific datasets the Compressed ISIC Dataset and the PH2 Dataset. The Compressed ISIC Skin Dataset, gathered by the ISIC, is a comprehensive collection of further than 25,000 dermoscopic images and associated metadata. It's an inestimable resource for skin cancer exploration and machine literacy enterprise. The dataset includes a variety of skin lesion images, similar as benign and nasty tubercles, rudimentary cell lymphomas, and scaled cell lymphomas, among others. Its different nature is pivotal for the effective training and conception of machine literacy models. The dataset's detailed lesion labeling by expert dermatologists is particularly salutary for supervised literacy models. The wide vacuity of the ISIC Skin Dataset has propelled exploration in areas like skin cancer bracket, lesion segmentation, and point analysis. It has also been necessary in benchmarking machine literacy algorithms. The dataset, primarily composed of 1800 benign operative images and 1497 nasty operative images, is a rich source for developing models that can visually separate between benign and cancerous intelligencers. Each image is formalized to a 224x224 pixel resolution in RGB format. The PH2 dataset, sourced from the Dermatology Service at Hospital Pedro Hispano are the other essential resource for skin cancer exploration and machine literacy operations. The dataset consists of 200 dermoscopic pictures of skin lesions, each meticulously annotated with medical information and unique image acquisition settings. This dataset offers a wealth of information for developing advanced exploration and machine literacy operations concentrated on skin cancer discovery and analysis. Datasets are abecedarian in training convolutional neural networks (CNNs) and other machine learning algorithms, as they supply the critical training data necessary for these models to fete and learn patterns. inadequate data can lead to ineffective literacy and poor model conception. This discussion focuses on two specific datasets the Compressed ISIC Dataset and the PH2 Dataset. The Compressed ISIC Skin Dataset, gathered by the International Skin Imaging Collaboration (ISIC), is a comprehensive collection of further than 25,000 dermoscopic images and associated metadata. It's an inestimable resource for skin cancer exploration and machine literacy enterprise. The dataset includes a variety of skin lesion images, similar as benign and nasty tubercles, rudimentary cell lymphomas, scaled cell lymphomas, among others. Its different nature is pivotal for the effective training and conception of machine literacy models. The dataset's detailed lesion labeling by expert dermatologists is particularly salutary for supervised literacy models. The wide vacuity of the ISIC Skin Dataset has propelled exploration in areas like skin cancer bracket, lesion segmentation, and point analysis. It has also been necessary in benchmarking machine literacy algorithms. The dataset, primarily composed of 1800 benign operative images and 1497 nasty operative images, is a rich source for developing models that can visually separate between benign and cancerous intelligencers. Each image is formalized to a 224x224 pixel resolution in RGB format.

The PH2 dataset, sourced from the Derma Service at Hospital Pedro, Portugal, is another essential resource for skin cancer exploration and machine literacy operations. It encompasses 200 dermoscopic images of skin lesions, each strictly annotated with medical details and specific parameters of image accession. This dataset offers a wealth of information for developing advanced exploration and machine literacy operations concentrated on skin cancer discovery and analysis.

3.2 Model Development and Deployment

The whole model of CNN will be developed and Deployed with these steps:

— Step 1: Import the required libraries. In the initial stage, you incorporate the necessary Python libraries, which provide you with the necessary tools and functions for your project. TensorFlow (sometimes referred to as Keras) is a library utilised for constructing and training neural network models. NumPy is employed for numerical computations, and additional libraries like as Pandas for data processing and Matplotlib for visualisation may also be utilised. These libraries are considered essential examples in the field.

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

— Step 2: Filling the Image Dictionary with Pictures and Labels: This is where you load the dataset, which most likely includes pictures of skin lesions. In order to generate a dictionary or other comparable data structure that maps each image to its label, these images are first read into a format suitable for processing (such as arrays) and then matched with their respective labels (such as benign or malignant).

— Categorical Labels in Step 3: The labels are transformed into a category format in this stage. For instance, one-hot encoding would be used to represent the two classifications (malignant and benign). Accordingly, a benign sample may be shown as [1, 0] and a malignant sample as [0, 1].

— Step 4: Acclimatization To make sure that pixel values are on a consistent scale, often between 0 and 1, image data is normalized. This helps the model handle the variability in the picture data more effectively, which enhances the model's convergence during training.

— Step 5: Divide the training and testing data into separate sets. The dataset is divided into two sets: a test set and a training set. The CNN model undergoes training using the training set, and its performance is evaluated using the test set. This division is crucial for assessing the model's ability to generalize to novel, untested data.

— Step 6: Building Models During this stage, the CNN structure is established. The conventional components of a Convolutional Neural Network The architecture of CNNs comprises convolutional, pooling, and fully linked layers. The specifications for the layers, including their order and characteristics such as the number of filters, kernel size, activation functions, etc., would be explicitly defined.

— Step 7: Examining both sides Model Reliability of the model is ensured through cross-validation. The training data is divided into multiple parts, the model is trained on some of the parts, and the remaining parts are used for validation. The model's performance is averaged over the course of multiple iterations of this process.

— Step 8: Testing of a model The test set is employed to evaluate the performance of the model after it has undergone training and validation. During this stage, the model's ability to function on data that it has not been exposed to during the training process is evaluated. Commonly utilized performance measurements include F1-score, recall, accuracy, and precision.

— Step 9: ResNet50 Implementation: A pre-trained model called ResNet50 is offered by Keras. It is renowned for having a deep architecture and residual connections, which facilitate the training of deeper networks. ResNet50 can be used as a foundation model, and it can be adjusted for your particular task (skin cancer detection). Retraining parts of the layers on your particular dataset while freezing others is the process of fine-tuning. These approaches provide a systematic approach to building a CNN model for a complex task like identifying skin cancer. Each every phase is crucial and contributes to the model's overall effectiveness and precision. The model's exceptional ability to detect skin cancer can significantly aid in early diagnosis and treatment, showcasing the significant impact of artificial intelligence and deep learning in the medical domain.

Due to the dataset's balanced nature, the model will be evaluated based on its accuracy score.

$$Accuracy \frac{True\ Positives\ (TP) + True\ Negatives\ (TN)}{Total\ Number\ of\ Cases (ALL)} \quad (1)$$

$$\text{F1 score} = 2 \times \frac{\text{positive predictive value} \times \text{sensitivity}}{\text{positive predictive value} + \text{sensitivity}} \quad (2)$$

In this formula:

— True Positives (TP) are situations in which the model correctly predicts the positive class. In the context of skin cancer detection, this refers to instances where the model accurately classifies a picture as depicting skin cancer.

— True Negatives (TN) are situations where the model correctly predicts the negative class. In the context of skin cancer detection, this refers to instances where the model accurately classifies an image as negative for skin cancer..

— Total Number of Cases (ALL) s the cumulative count of all cases in the dataset, encompassing True Positives, True Negatives, False Positives (cases mistakenly recognized as having the condition), and False Negatives (cases mistakenly identified as not having the condition).

— Accuracy is an important indicator for assessing the overall efficacy of a model. However, it is essential to include additional metrics such as recall, F1-score and precision, in order to acquire a comprehensive picture. This is particularly relevant in medical contexts, where misclassification can have significant consequences.

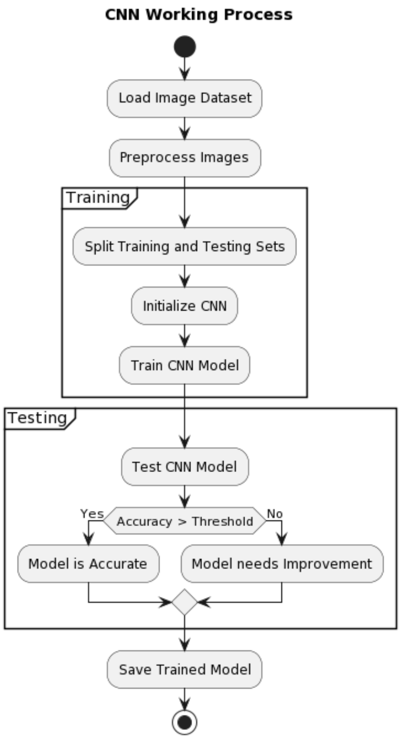

Fig. 3. CNN Working Activity Diagram

3.3 Training

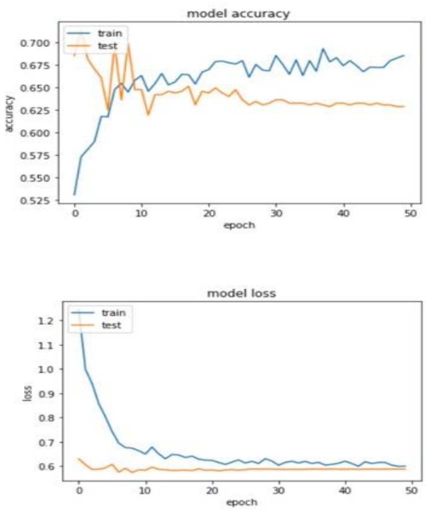

Fig. 4. CNN Model Accuracy and Loss

Model Accuracy Graph

Training Accuracy (blue line): This line represents the model's accuracy on the training data. The accuracy fluctuates over time, which can be a sign of the model struggling to learn from the data or the presence of noisy data. There is a significant spike and dip around epoch 5, which could indicate an issue with the data, a learning rate that is too high, or some instability in the training process.

Testing Accuracy (orange line): The testing accuracy, while generally increasing, also shows some volatility. It does not match the training accuracy closely, which typically means the model isn't generalizing as effectively as desired. The fluctuations and lower overall accuracy could suggest that the model is having difficulty learning the patterns within the data or that the test set may contain challenging or previously unseen examples.

Model Loss Graph

Training Loss (blue line): The training loss decreases sharply initially, suggesting that the model is learning from the training data. After the initial drop, the loss continues to decline but at a much slower rate, which is expected as the model begins to converge on a solution.

Testing Loss (orange line): The testing loss mirrors the training loss's sharp initial decrease. However, it plateaus much earlier than the training loss. This could indicate that while the model is improving its performance on the training data, it's not translating that learning as effectively to the test data.

Observations and Possible Actions

— Fluctuations in Accuracy and Loss: The significant fluctuations in the model accuracy, especially in the test curve, suggest that the model might be sensitive to certain data points or that there is noise in the dataset. One might look into smoothing these fluctuations by adjusting the learning rate, adding dropout, or using batch normalization.

— Generalization Gap: The gap between the training and testing curves in both graphs suggests that the model may be overfitting the training data. Introducing regularization, increasing data augmentation, or collecting more data could help mitigate this.

Plateauing of Test Loss: The test loss plateauing while the training loss continues to decrease is another indication of overfitting. It's essential to monitor this and perhaps implement early stopping to halt training when the test loss stops improving. To

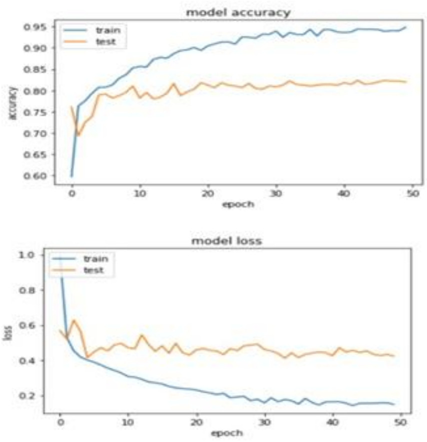

Fig. 5. ResNet50 Model Accuracy and Loss

summaries, these graphs demonstrate that the model has difficulties in maintaining accuracy stability and avoiding overfitting during the learning process. In order to enhance the model's ability to extrapolate to unfamiliar data and establish a more consistent learning approach, more measures would be required. The upper picture illustrates the model loss and accuracy of the CNN method. The graphic shown in Fig 4 clearly demonstrates that the model is not suitable for this particular task. Hence, we will further employ another analogous technique built upon the Convolutional Neural Network (CNN) called ResNet50. The graph shown in Fig 5 represents the outcome we will obtain thereafter.

Model Accuracy Graph

This graph illustrates the accuracy of the model on both the training set (train) and the test set (test) across 50 epochs: Training Accuracy (blue line): This line indicates the level of precision of the model when applied to the training dataset. The observed trend indicates a progressive growth, implying that the model is acquiring knowledge and improving its ability to forecast the training data.

Testing Accuracy (orange line): This line represents the accuracy on the test dataset. It also increases over time but at a slower rate than the training accuracy. This is typical as the model is trained to perform well on the training data.

The gap between the training and testing accuracy indicates the presence of some overfitting, where the model performs better on the training data compared to the test data. However, the test accuracy is still increasing, which is a good sign that the model is generalizing well.

Model Loss Graph

This graph illustrates the model's loss on both the training and test datasets during 50 epochs. Training Loss (blue line): The loss decreases sharply at the beginning and continues to decline over time, leveling off as the epochs increase. This indicates the model is increasingly fitting the training data well.

Testing Loss (orange line): Although it tends to plateau or drop more slowly, the test loss of data reduces in tandem with the training loss. Like the accuracy graph, this shows the model is learning and improving its predictions on the test set.

The model loss graphs tend to mirror the accuracy graphs but in the opposite direction, as lower loss corresponds to higher accuracy.

In both graphs, the fact that the test lines (accuracy and loss) follow the trends of the training lines (though not as closely) suggests that the model is learning features that generalize beyond just the training data, which is crucial for a successful model that can perform well on unseen data. However, to further improve the model's performance, one might consider techniques to reduce overfitting, such as regularization, dropout, or further data augmentation. In Summary, there isn't a one-size-fits-all answer to which CNN architecture is the best for skin cancer detection. The choice between ResNet50 and other CNN architectures should be based on the specific characteristics of your problem and resources. The best approach is often to try multiple architectures and configurations, then choose the one that provides the best trade-off between performance and resource utilization.

Additionally, we can also use Resnet101. Among the many picture classification jobs that ResNet101[16] excels at, one of the most difficult is detecting skin cancer. With its 101-layer design, the model can learn a wide range of features at different levels of complexity. This level of detail is especially helpful for medical picture analysis, where minute variations are crucial. The training of this deep network is made possible by the model's residual learning architecture, which is distinguished by skip connections and successfully addresses the vanishing gradient issue. Furthermore, transfer learning, which involves refining a model that has been pre-trained on large datasets like ImageNet to specialize in skin cancer pictures, demonstrates the versatility of ResNet101. This procedure improves the accuracy of the model and shortens the training time. ResNet101 is a great asset in the field of medical imaging because of its shown track record of good performance in identifying skin lesions, which reinforces its reputation as a dependable instrument for the early identification and treatment of skin cancer.

4. PRACTICAL APPLICATION

Skin cancer prediction using convolutional neural networks (CNNs) holds immense potential for practical applications in the medical field, particularly in the areas of dermatology, oncology, and preventive healthcare.

Here's a detailed overview of the potential applications and their impact:

Dermatology:

The use of CNN in predicting cancer has the capacity to transform the field of dermatology by offering automated and precise analysis of skin lesions. This technology aids in the prompt detection, treatment, and prevention of skin cancer.

Early Skin Cancer Detection:

CNN-based tools can assist dermatologists in identifying suspicious lesions early, enabling timely intervention and improved treatment outcomes. By analyzing skin images, CNNs can detect subtle patterns and features that may be indicative of skin cancer, even in its early stages. This early detection can significantly improve the chances of successful treatment and reduce the risk of metastasis.

Teledermatology:

CNNs can enhance teledermatology services by providing remote assessment of skin lesions, expanding access to expert care for patients in remote or underserved areas. With the increasing availability of high-quality skin imaging devices, patients can capture images of their lesions and transmit them to dermatologists for analysis. CNNs can then analyze these images and provide preliminary assessment, allowing dermatologists to prioritize cases and focus their attention on those with the highest likelihood of malignancy.

Dermoscopy Image Analysis:

Dermoscopy is a non-invasive technique that utilizes a special hand-held microscope with polarized light to examine skin lesions in greater detail. Dermoscopic images often contain complex patterns and subtle features that can be difficult for human experts to interpret consistently. CNNs can analyze dermoscopic images with high accuracy, extracting relevant features and providing a second opinion to dermatologists. This can improve the chances of skin lesion detection and reduce the risk of misdiagnosis. Conventional Image Analyzer(CIA) was used as a method for creating a diagnosable image of Cancerous Skin Lesion when for Dermoscopy. However, as researched by researchers Kathrina et el.[13], they present that CNN Outperforms CIA for image classification. The image attached below is a researched proof of the statement. In the image below, (A) is Basic Test Dermoscopic Image, (B) is the graph for that Dermoscopic Image, (C) is the Improved CNN Dermoscopic Image and (D) is the graph for the Improved CNN Dermoscopic Image shown in Fig 6.

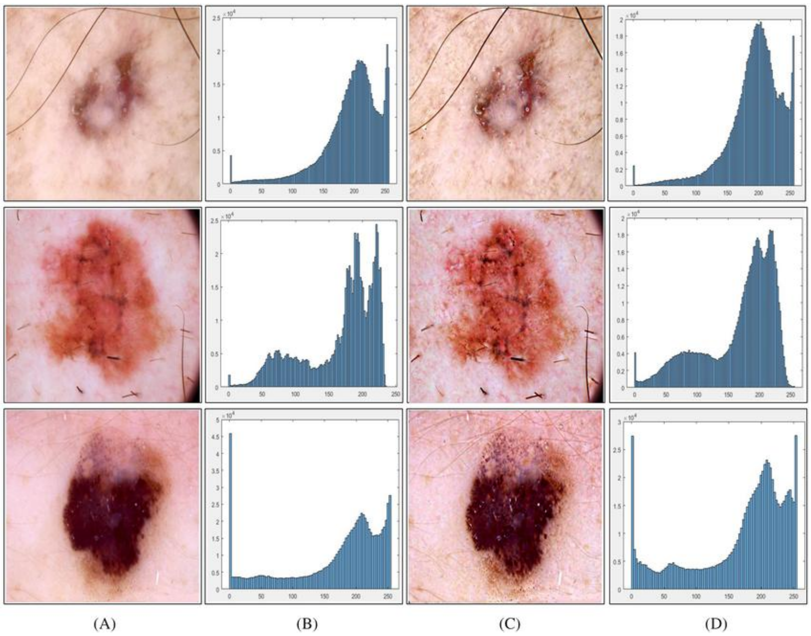

Fig 6 Traditional Dermoscopy VS CNN Dermoscopy

Skin Cancer Screening:

CNN-based tools can be integrated into screening programs, facilitating the identification of at-risk individuals and encouraging early diagnosis. Lesion screening is crucial for early detection and sustainable results, but traditional screening methods can be time-consuming and subjective. CNNs can analyze large numbers of skin images quickly and objectively, identifying suspicious lesions that warrant further evaluation by a dermatologist. This can significantly increase the efficiency and accuracy of skin cancer screening programs.

Oncology:

CNNs has a huge capability to play a significant role in oncology by providing advanced tools for melanoma diagnosis, prognosis assessment, and personalized treatment planning.

Melanoma Diagnosis and Prognosis:

CNNs can assist oncologists in classifying melanomas and predicting their prognosis, guiding treatment decisions and improving patient outcomes. By analyzing melanoma images, CNNs can identify features that are associated with different stages and subtypes of melanoma, allowing oncologists to tailor treatment strategies to each patient's individual risk factors.

Personalized Treatment Planning:

CNN-based analysis of skin lesions can provide personalized treatment recommendations, optimizing therapeutic strategies for each patient. By considering factors such as the lesion's type, stage, and location, CNNs can help oncologists select the most appropriate treatment options for each patient, maximizing the likelihood of successful treatment and minimizing the risk of side effects.

Monitoring of Skin Cancer Treatment:

CNNs can monitor skin lesions during treatment, tracking their response and identifying potential recurrence or progression. By analyzing post-treatment skin images, CNNs can detect subtle changes in lesion characteristics that may indicate a recurrence or progression of the disease. This early detection can prompt oncologists to intervene promptly and adjust treatment plans as needed.

5. FUTURE DEVELOPMENT

The future development of Convolutional Neural Networks (CNNs) for skin cancer detection holds immense potential for advancing medical diagnostics. One key area of development is the refinement of algorithms to enhance accuracy, particularly in distinguishing between various types of skin lesions. This improvement could result from incorporating larger and more diverse datasets, including images Encompassing a diverse array of skin tones and disorders, to reduce biases and improve the model's generalizability. Another promising direction is the integration of CNNs with personalized medicine approaches. By combining image analysis with patient-specific data such as genetic information, personal medical history, and lifestyle factors, the models could provide more tailored and accurate assessments. There is also significant scope for technological advancements, such as developing portable, user-friendly devices for real-time skin monitoring and analysis, which could be particularly beneficial for individuals at high risk or living in remote areas. Ensuring these technologies undergo rigorous clinical trials and obtain necessary regulatory approvals is crucial for their safe and effective integration into healthcare practices. Furthermore, given the sensitive nature of medical data, future developments must prioritize Implement stringent data privacy and security protocols to safeguard patient information. Finally, fostering interdisciplinary collaborations among technologists, clinicians, data scientists, and ethicists will be vital in navigating the complexities of implementing these advanced systems in a clinical setting. These developments not only provide the potential to improve the precision and availability of skin cancer diagnosis, but also lay the groundwork for breakthroughs in wider healthcare applications.

6. CONCLUSION

In summary, this research project aimed to enhance early skin cancer detection through the implementation of a specialized Convolutional Neural Network (CNN). Motivated by the urgency of timely diagnosis and the limitations of conventional methods, the study meticulously curated a diverse dataset and devised a custom CNN architecture. Notably, the proposed model outperforms the established ResNet50, a widely used architecture, in skin cancer image classification. The custom CNN's superior accuracy and precision underscore its efficacy in capturing intricate lesion patterns, emphasizing the importance of task-specific model design in medical image analysis. These findings contribute to the ongoing discourse on automating skin cancer diagnosis, offering a nuanced and promising avenue for advancing clinical practices and potentially revolutionizing the landscape of dermatological care.

REFERENCES

1. Melanoma skin cancer statistics. (n.d.). American Cancer Society. https://www.cancer.org/cancer/types/melanoma-skin-cancer/about/key-statistics.html
2. World Health Organization: WHO. (2022, February 3). Cancer. https://www.who.int/news-room/fact-sheets/detail/cancer
3. What are the symptoms of skin cancer? | CDC. (n.d.). https://www.cdc.gov/cancer/skin/basic_info/symptoms.htm#print
4. Skin cancer (Including Melanoma)—Patient version. (n.d.). National Cancer Institute. https://www.cancer.gov/types/skin
5. Sekaran, R., Al-Turjman, F., Patan, R., & Ramasamy, V. (2023). Tripartite transmitting methodology for intermittently connected mobile network (ICMN). ACM Transactions on Internet Technology, 22(4), 1-18.
6. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., & Rabinovich, A. (2015). Going deeper with convolutions. 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 1–9. https://doi.org/10.1109/CVPR.2015.7298594
7. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 770–778. https://doi.org/10.1109/cvpr.2016.90
8. Sekaran, R., Munnangi, A. K., Ramachandran, M., & Gandomi, A. H. (2022). 3D brain slice classification and feature extraction using Deformable Hierarchical Heuristic Model. Computers in Biology and Medicine, 149, 105990-105990., 8, 7160–7172. https://doi.org/10.1109/access.2019.2962812
9. Ramesh, S. (2017). An efficient secure routing for intermittently connected mobile networks. Wireless Personal Communications, 94, 2705-2718.
10. Babino, G., Lallas, A., Agozzino, M., Alfano, R., Apalla, Z., Brancaccio, G., Giorgio, C. M., Fulgione, E., Kittler, H., Kyrgidis, A., Papageorgiou, C., & Argenziano, G. (2021). Melanoma diagnosed on digital dermoscopy monitoring: A side-by-side image comparison is needed to improve early detection. Journal of the American Academy of Dermatology, 85(3), 619–625. https://doi.org/10.1016/j.jaad.2020.07.013
11. Saravanakumar, S., & Thangaraj, P. (2019). A computer aided diagnosis system for identifying Alzheimer's from MRI scan using improved Adaboost. Journal of medical systems, 43(3), 76.
12. Kumaresan, T., Saravanakumar, S., & Balamurugan, R. (2019). Visual and textual features based email spam classification using S-Cuckoo search and hybrid kernel support vector machine. Cluster Computing, 22(Suppl 1), 33-46.
13. Saravanakumar, S., & Saravanan, T. (2023). Secure personal authentication in fog devices via multimodal

rank-level fusion. Concurrency and Computation: Practice and Experience, 35(10), e7673.

14. Thangavel, S., & Selvaraj, S. (2023). Machine Learning Model and Cuckoo Search in a modular system to identify Alzheimer's disease from MRI scan images. Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, 11(5), 1753-1761.

15. Saravanakumar, S. (2020). Certain analysis of authentic user behavioral and opinion pattern mining using classification techniques. Solid State Technology, 63(6), 9220-9234.

16. Hasan, M. K., Elahi, M. T. E., Alam, M. A., Jawad, M. T., & Martí, R. (2022). DermoExpert: Skin lesion classification using a hybrid convolutional neural network through segmentation, transfer learning, and augmentation. Informatics in Medicine Unlocked, 28, 100819. https://doi.org/10.1016/j.imu.2021.100819

17. Haggenmüller, S., Maron, R. C., Hekler, A., Utikal, J., Barata, C., Barnhill, R. L., Beltraminelli, H., Berking, C., Betz-Stablein, B., Blum, A., Braun, S. A., Carr, R., Combalia, M., Fernández-Figueras, M., Ferrara, G., Fraïtag, S., French, L. E., Gellrich, F. F., Ghoreschi, K., . . . Brinker, T. J. (2021). Skin cancer classification via convolutional neural networks: systematic review of studies involving human experts. European Journal of Cancer, 156, 202–216. https://doi.org/10.1016/j.ejca.2021.06.049

18. Naqvi, M., Gilani, S. Q., Syed, T., Marques, O., & Kim, H. C. (2023). Skin Cancer Detection Using Deep Learning—A Review. Diagnostics, 13(11), 1911. https://doi.org/10.3390/diagnostics13111911

19. Dildar, M., Akram, S., Irfan, M., Khan, H. U., Ramzan, M., Mahmood, A. R., Alsaiari, S. A., Saeed, A. H. M., Alraddadi, M. O., & Mahnashi, M. H. (2021). Skin Cancer Detection: A Review Using Deep Learning Techniques. International journal of environmental research and public health, 18(10), 5479. https://doi.org/10.3390/ijerph18105479

20. Gouda, W., Sama, N. U., Al-Waakid, G., Humayun, M., & Jhanjhi, N. Z. (2022). Detection of skin cancer based on skin lesion images using deep learning. Healthcare, 10(7), 1183. https://doi.org/10.3390/healthcare10071183

21. R, N. S., Shrivastava, V. K., & Parvathi, K. (2021). Multiclass skin lesion classification using image augmentation technique and transfer learning models. International Journal of Intelligent Unmanned Systems. https://doi.org/10.1108/ijius-02-2021-0010