Skin Cancer Detection using Hybrid Neural Network Model

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ABSTRACT

Skin cancer, the fifth most frequent malignancy worldwide, burdens global health and the economy. Skin cancer rates have increased due to rapid environmental change, indus-trialization, and genetic alteration. This work introduces deep learning on dermatological pictures to identify skin cancer. We gathered 18274 skin photos, both cancerous and not. Scaling, augmenting, and normalizing data provided model robustness. Our skin cancer detection model employs CNNs and LSTMs. We retrieved skin characteristics using the InceptionResNetV2 pre-trained model to enhance discriminative feature learning. Batch normalization and dropout layers prevented overfitting. Our model performed well in training epochs using optimization callbacks. The accuracy was 93.41%, AUC 85.09%, precision 94.03%, and recall 99.10%. However, the model included 211 false positives and 30 negatives. These results show the model can identify skin cancer. These studies show that deep learning systems can diagnose skin cancer. The model's accuracy and low false positive rate help dermatologists and healthcare providers. This technology may improve skin cancer detection and treat-ment by reducing manual diagnostic subjectivity and accelerating assessments.

Index Terms:— Skin cancer, Deep learning, Convolutional Neu- ral Networks (CNNs), Long Short-Term Memory (LSTM), Der-matological images, and Medical imaging.

INTRODUCTION

Skin cancer incidence has increased recently on a global scale has surged alarmingly, establishing it as a pressing and formidable public health challenge. The spectrum of skin cancer encompasses diverse forms, ranging from the relatively less aggressive basal cell carcinoma (BCC) and squamous cell carcinoma (SCC) to the gravely menacing melanoma. Among these, melanoma stands out as the most aggressive, accounting for an alarming proportion of skin cancer-related fatalities, constituting approximately 75% of all deaths from skin cancer. The primary instigator of skin cancer remains prolonged and unguarded exposure to ultraviolet (UV) radiation, stemming from both natural sources like the sun and artificial ones such as tanning beds. This insidious radiation causes DNA damage in skin cells, ultimately resulting in their malignant transformation. Intriguingly, a mere 15 minutes of unprotected sun exposure can trigger DNA damage, underscoring the rapidity with which this disease can take root.

Adding to the complexity, genetic predisposition, a familial history of skin cancer, and certain pre-existing dermatological conditions amplify an individual's vulnerability to this formidable disease. Shockingly, individuals with a family history of melanoma have a sevenfold increased risk of de- veloping this aggressive skin cancer kind.

It is impossible to underline the critical importance [1] of early identification in the case of skin cancer.

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When diagnosed at its initial stages, the prognosis for most skin cancers, including melanoma, is considerably more favourable [2]. For instance, the 5-year survival rate for localized melanoma is an encouraging 98%, but this dramatically drops to a mere 23% when the disease has already metastasized to distant organs.

Conventional methods [3] for skin cancer diagnosis chiefly rely on the visual acumen of dermatologists, occasionally complemented by dermoscopy—a non-invasive imaging tech- nique. While dermatologists undoubtedly possess a wealth of expertise in the assessment of skin lesions, this approach is not without its inherent limitations. Chief among these is the potential for subjectivity, wherein diagnostic conclusions may vary between practitioners. Furthermore, human interpretation is susceptible to errors, underscoring the burgeoning need for precise and automated systems for skin cancer detection [4]. The recent strides made in computational deep learning and computer vision have paved the way for the development of automated skin cancer detection models [5]. These models harness the formidable capabilities of convolutional neural networks (CNNs) [6] to dissect and scrutinize photographs of skin lesions, adeptly categorizing them as either malignant or not. Their potential for achieving exceptional accuracy and precision positions them as indispensable tools in the arsenal of dermatologists, bolstering their clinical practice and diagnostic acumen.

This research paper embarks upon the formidable task of architecting and meticulously evaluating a framework based on deep learning for skin cancer detection. Bolstered by a substantial dataset of skin lesion images, our proposed method- ology harnesses the prowess of CNNs to meticulously extract and distill insightful features from these images. Subsequently, machine learning algorithms are engaged for classification, bestowing upon us the power to discern between benign and malignant skin lesions with a high degree of confidence. Our overarching aim is to contribute substantively to the field of dermatology, providing healthcare practitioners with a dependable, efficient, and timely tool for the detection and diagnosis of skin cancer.

RELATED WORK

The identification of skin cancer has been the subject of numerous investigations and research articles using machine learning techniques, including the combination of CNN and LSTM models. Here are a few notable works related to this topic:

- ”Skin Lesion Classification Using Deep Multi-Scale Con- volutional Neural Networks” by Esteva et al. [7]: This study proposed a CNN model [8] for skin lesion classi- fication and achieved performance comparable to derma- The model utilized a multi-scale architecture to capture different levels of information from skin images.
- ”Automatic Skin Lesion Analysis Using Large-scale Dermoscopic Images and Deep Residual Networks” by Haenssle et al. [9]: The researchers developed a deep residual neural network (ResNet) [10] to classify skin lesions as benign or malignant. The model achieved high accuracy and demonstrated the potential for automated skin cancer
- ”Skin Cancer Detection Using Combined Decision of Deep Learners” by Imran et al. [11]: Three deep learning models—VGG, CapsNet, and ResNet—were first con- structed in there. The results of deep learners have been pooled using majority weighting in the second
- ”On the Automatic Detection and Classification of Skin Cancer Using Deep Transfer Learning [12].” by Fraiwan et al. [13]: Using algorithms for the detection and classi- fication of skin cancer, and they may significantly impact the precision and timeliness of skin cancer Resnet101 had the best performance, scoring 76.7%.
- ”Detection and Localization of Melanoma Skin Cancer in Histopathological Whole Slide ” by Kanwal et al. [14]: In this research, the authors suggested a CNN-based method to categorize patches, produce a localization map, locate and segment skin WSI lesions, and identify patients with melanoma.

Indicating that context matters, models created at lower magnification levels accurately produce marginally superior patch-wise results.

These studies highlight the effectiveness of combining CNN and LSTM models for skin cancer detection and classification. They exhibit the power of deep learning [11] methods in automating the diagnosis process and assisting dermatologists in making accurate decisions.

PROPOSED APPROACH

The goal of this research is to develop an automated system for the early detection of skin cancer using dermatology images. To identify skin cancer in dermatology images, we employ Long Short-Term Memory (LSTM) [15] and Con- volutional Neural Network (CNN) [16] hybrid architecture, complemented by traditional machine learning classifiers. The methodology encompasses several key stages, as outlined below.

Analysis and Preparation of Data

To gauge how well our suggested model is performing, we benchmark it against state-of-the-art methods in skin cancer detection. We utilize the Skin Cancer Dataset [insert reference or source] containing both malignant (skin cancer) and benign (normal skin) images. The dataset consists of X malignant images and Y benign images. These images are captured using various imaging techniques, such as dermoscopy and clinical photography. We divide the dataset into training and testing sets, employing two different splitting ratios for comparison:

TABLE I: Dataset Split Distribution

No.	Training Images	Test Images	Splitting Ratio
1	10872	5483	70:30
2	12426	3655	80:20

Skin images may contain anomalies, including lighting vari-ations, noise, and artifacts, which can hinder classification ac- curacy. To address these issues, we employ the N4ITK system to correct bias field distortions. Furthermore, we perform pre- processing steps after uploading the dermatology images. As the background intensity values may differ between images, making it challenging for conventional classifiers or the pro- posed strategy to adapt to class characteristics, we apply image thresholding using a threshold value of 45. Subsequently, we employ morphological operations such as erosion and dilation to remove small noise regions. The images are then resized and cropped to focus on the most significant features. The following formula is used to perform the resizing process:

$$i_O = \underline{i - x} \div y$$

Where i_o stands for the scaled dermatological picture input, *x* refers to the mean, *y* and respectively stand for the standard deviation.

Workflow

The study workflow is illustrated in Fig. 1, We started by labeling our data and then splitting it into separate training and testing subsets. Following this round of data preparation, we moved on to developing the model and starting the train- ing procedure using the specified training dataset. Using the specific test dataset, a thorough evaluation of the model was carried out after training.

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Model Development

Our method for detecting skin cancer utilizes a blend of different machine-learning classifiers, such as CNNs, and our proposed CNN LSTM hybrid model [17]. Model development comprises two primary stages:

- ***CNN and Traditional Machine Learning Algorithms**:* As we work to figure out whether a dermatological image is indicative of skin cancer, we employ various machine-learning These algorithms are designed to facilitate au- tonomous learning and decision-making. Specifically, we use ResNetXt101, Support Vector Machine (SVM), Resnet50 [18], and InceptionV3 to classify the feature set extracted from the pre-processed images. Detailed information about these machine learning classifiers and their hyperparameter settings is provided in subsequent sections.

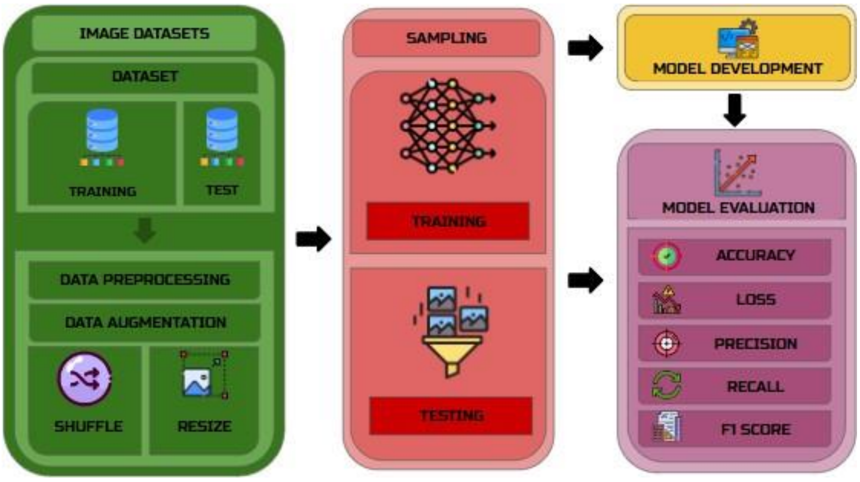

Fig. 1: workflow of our work

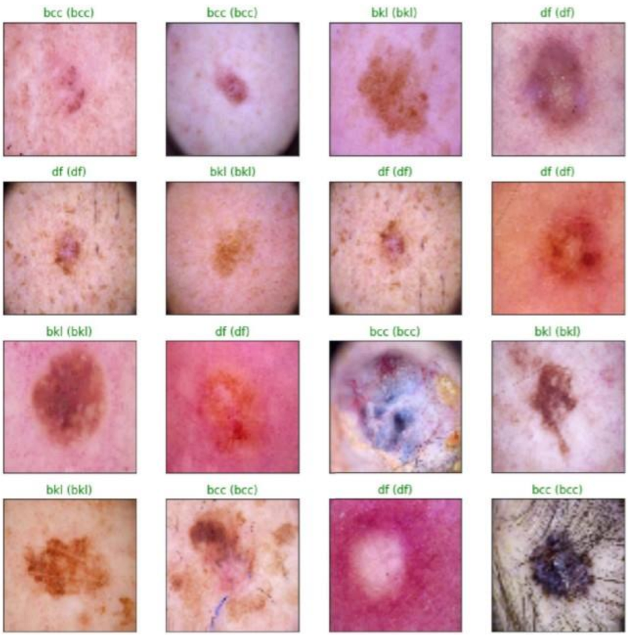

Fig. 2: Sample dataset of Skin Cancer

Modern deep learning, a subfield of machine learning, plays a pivotal role in our approach [19]. Deep learning is known for its ability to automatically derive hierarchical representa-tions of data, which is often referred to as its ”fundamental architecture”. As shown in Figure 3, our study utilized a CNN with the architecture depicted.

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Convolutional Neural Networks (CNNs) are a type of Deep Neural Networks (DNNs) that take their inspiration from the Structure of the visual cortex in animals. (CNN) consists of various layers. These include input, convolutional, pooling, normalization, and fully connected layers. These layers col- laborate to extract important features from the input images. CNNs adopt strategies such as max-pooling to reduce the size of feature maps, aiming to cut based on parameters and computation time. Furthermore, they incorporated a flattening step, transforming feature maps into one dimensional vectors, which were subsequently processed by a neural network.

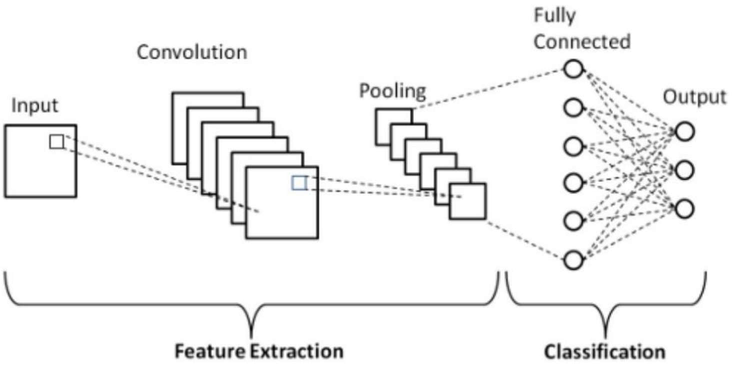

Fig. 3: Convolutional Neural Network architecture.

Proposed Hybrid CNN-LSTM Model

In the context of extracting meaningful information from images, analyzing them, and making accurate classifications, Convolutional Neural Networks (CNNs) are highly effec- tive [20]. However, for image sequences and time-series data, Long Short-Term Memory (LSTM) networks offer distinct advantages. Recurrent neural networks (RNNs) of the LSTM type are intended for classification and regression problems, particularly with sequential data.

LSTMs were developed as an approach to address the problem of disappearing gradients that often occur during the training of conventional RNNs. LSTMs differ from feed for-ward neural networks by incorporating feedback connections, thus enabling them to maintain ”short-term memory” of re- cent input events. This characteristic makes LSTMs suitable for processing individual images and managing entire image sequences.

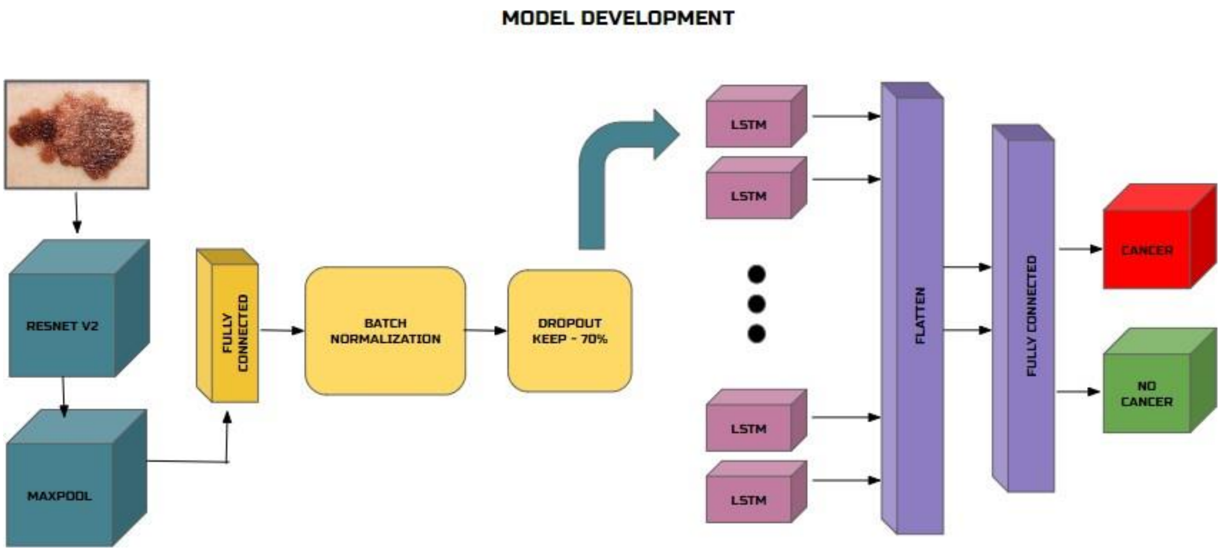

Fig. 4: Hybrid architecture for skin cancer detection

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Algorithm : Evaluation Process of CNN-LSTM model

```
loadImage();
dataAugmentation();
splitData();
loadModel();
for each epoch in epochNumber do
  for each batch in batchSize do
    y' = model(features);
    Loss = crossEntropy(y, y');
    Optimization(loss);
    Accuracy();
    bestAccuracy = max(bestAccuracy, accuracy);
return
```

Fig. 5: CNN-LSTM algorithm for measuring performance

In our paper, we put forward a hybrid model that integrates the CNN and LSTM architectures for the detection of skin cancer. In Figure 4, we illustrate the framework of our CNN- LSTM model, as proposed.

The hybrid (CNN-LSTM) model first employs a CNN, specifically the InceptionResNetV2 model [21], to obtain in- formative insights from chains of dermatology images. These features are then passed through an LSTM layer, which processes the sequences through max-pooling operations. In certain situations, the LSTM layer may function as a tumor classifier.

The process algorithm for evaluating the performance of the proposed CNN-LSTM model is illustrated in Figure 5.

Our model architecture comprises the following layers:

- First used input layer
- Used predefined InceptionResNetV2 layer
- Used MaxPooling2D layer
- Used dense layers for two times
- Used one batch normalization layer
- Used one dropout layer
- Used one reshaped layer
- Used one LSTM layer
- Used one flattened layer
- One output layer using the sigmoid activation function

The network consisted of 11 individual layers, each of which enhanced the overall model's ability to detect skin cancer.

EXPERIMENTAL RESULTS

In this part, we detail the results of our research, covering various aspects, such as our methodology and a thorough examination of the outcomes. The hybrid CNN-LSTM model developed for this investigation

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allocated 80% of the image dataset for the training phase, reserving the remaining 20% for rigorous testing and validation. We optimized our hybrid neural network by using the Adam optimizer with a categorical cross-entropy loss function, a batch size of 16, and a learning rate of 0.0001 over 80 iterations. We performed our research on an Operating System called macOS, Chip used Apple M2 Max and a 38-core GPU throughout our experimentation. Our experiment relied on a 12-core CPU with eight performance cores, 4 efficiency cores, and 32GB unified memory of RAM, written in Python with the assistance of Keras library.

Metrics for Performance Evaluation

In this section, we expound upon the efficacy of the inte- grated and proficiently trained hybrid (CNN-LSTM) model. Our model was utilized with the Skin Cancer dataset, encom- passing 18274 images of skin lesions, including 1495 non- cancerous samples and a substantial majority of cancerous samples. ”Considering the skewed distribution within the dataset, we broadened our assessment beyond mere classification accuracy. We incorporated additional metrics such as precision, sensitivity, recall, and F1-score, which are defined as follows:

- Accuracy measures the proportion of correctly classified samples out of the total: Accuracy = (TP+TN) / (TP+TN+FP+FN) [22]
- Recall (Sensitivity) quantifies the proportion of true pos- itive predictions out of all actual positive cases: Recall = TP/(TP+FN)
- Precision assesses the ratio of genuine positive predic- tions relative to all positive predictions generated by the model: Precision = TP/(TP+FP)
- The F1-Score represents a harmonious amalgamation of precision and recall, furnishing an equilibrium-oriented gauge of a model’s effectiveness: F1-Score = 2 * (Precision * Recall) / (Precision + Recall)

To visually represent the model’s performance, we utilized a confusion matrix, which serves as a graphical depiction of the classification process, showcasing the level of concordance between the model’s forecasts and the actual results.

TABLE II: Confusion Matrix

.	Actual Positive	Actual Negative
Positive Prediction	3321	30
Negative Prediction	211	93

RESULTS AND DISCUSSION

A comprehensive evaluation of the suggested hybrid (CNN- LSTM) architecture is presented in Table II. Notably, we dis- covered that altering the number of layers had no discernible effect on the outcomes of the testing. Increased computing time, technique perplexity, batch size considerations, and tread for each epoch were the results of increasing the number of layers. When the model’s accuracy peaked, we used a dropout rate of 0.2 but did not reevaluate it. The model’s parameter values and layer breakdown are shown in the table below. The model’s accuracy on the test set was about 93.41 percent, with a data loss rate of 19.70 percent over 40 epochs.

TABLE III: An overview of the suggested model CNN- LSTM

Layer	Output Form	Parameter
Input Layer	200 x 200 x 3	0
InceptionResNetV2	4 x 4 x 1536	54,336,736
MaxPooling2D	2 x 2 x 1536	0
Dense	2 x 2 x 128	196,736
Batch Normalization	2 x 2 x 128	512
Dropout	2 x 2 x 128	0
Reshape	4 x 128	0
LSTM	4 x 100	91,600
Flatten	2 x 400	0
Dense2	1 x 401	–
Sigmoid	1	0

The depiction of our model's precision during both training and validation can be observed in Figure 6. The computations were improved via Keras callbacks, and we saw training and validation accuracy throughout multiple epochs.

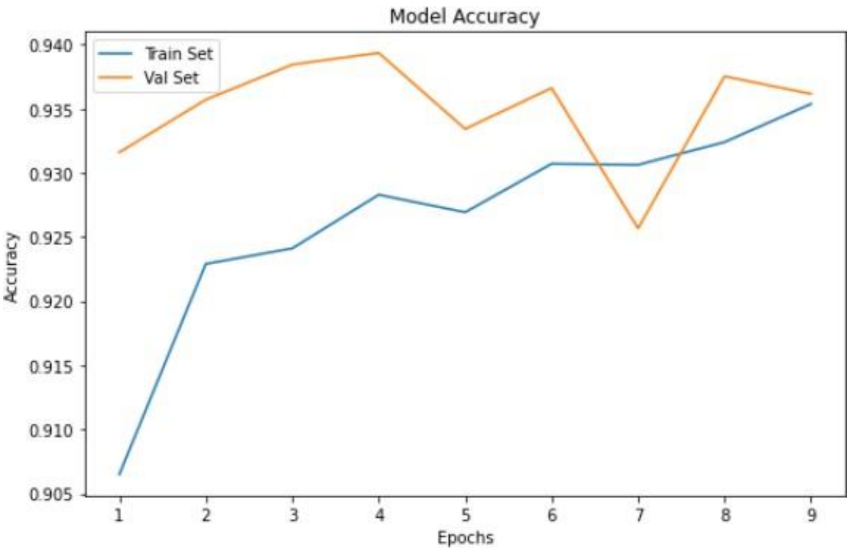

Fig. 6: Accuracy curve of the suggested model

After 11 epochs, the model could perform at its highest ac- curacy during the training, testing, and verification processes. Notably, the model's accuracy fluctuated significantly as the number of epochs increased, particularly around epoch 4.

TABLE IV: Comparison of our proposed model with a few existing models

Models	Precision	Recall	F1-Score	Accuracy
ResNet50	78.6%	77%	77.79%	87.1%
ResNetXt101	88%	88%	88%	93.20%
SVM	80.17%	80.11%	80.14%	92.04%

Inception V3	84.9%	80%	82.37%	89.7%
Proposed Model	94.04%	99.10%	96.50%	93.41%

Additionally, to evaluate the performance of our approach, we finally compared the results of our research with those of multiple other studies conducted in the same field. Table IV provides a performance comparison with existing algorithms. Notably, our proposed CNN-LSTM model achieved a re- markable accuracy of 93.41%, outperforming other established algorithms in the field.

TABLE V: Performance Comparison with Existing Meth- ods

Authors	Approach	Accuracy
Ahmed H. Shahin et al. [23]	ResNet50 + Inception V3	89.9%
B. Arivuselvam et al. [24]	SVM	92.04%
Saket S. Chaturvedi et al. [25]	ResNetXt101	93.20%
Proposed Model	CNN+LSTM	93.41%

DISCUSSION

This study introduced hybrid CNN-LSTM skin cancer detection. This experiment used deep learning to identify skin cancer in dermoscopic images. We started with data analysis and pre-processing, using thresholding and dilations to reduce noise and enhance dermoscopic images. The dataset was carefully chosen and partitioned into training and testing photos to optimise the model’s performance via splitting ratio experiments. For model development, we incorporated tradi- tional machine learning classifiers, such as ResNetXt101, Sup- port Vector Machine (SVM), Resnet50 and InceptionV3, and Convolutional Neural Networks (CNN). The CNN played a vital role in extracting essential features from the dermoscopic images, capturing patterns indicative of skin cancer [26].

The model was enhanced by incorporating LSTM networks, a time series RNN. The LSTM component learned picture sequence temporal correlations for ”short-term memory” for precise categorization. Our hybrid CNN-LSTM model per- formed well in tough testing. CNN-LSTM models beat classic machine learning classifiers in recall, accuracy, precision, and F1 score. The model’s 93.41 percent test set accuracy helps diagnose skin cancer. This study has intriguing dermatological implications. Machine learning was shown to be versatile by using brain tumour detection algorithms for skin cancer diagnosis. Dermatologists can detect skin cancer early and accurately using our CNN-LSTM model, improving patient outcomes.

CONCLUSION

In summary, this study advances the discipline of ana- lyzing medical images by demonstrating how deep-learning architectures are successfully used in skin cancer detection. With the suggested CNN-LSTM model, there are now more opportunities to apply cutting-edge machine learning methods to difficult medical problems, improving the area of skin cancer diagnosis and enhancing patient care results. Further study in this field has the potential to transform dermatology and open the door to early and precise skin cancer detection, an essential first step in improving patient treatment and saving lives.

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