

Automatically Early Detection of Skin Cancer using Hybrid Neural Network Models

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Abstract – The prevalence of skin cancer is increasing globally, rendering it one of the most prevalent forms of cancer in humans. This occurs when cells proliferate uncontrollably due to anomalous DNA modifications. The probability of effective treatment for skin cancer significantly rises with early detection, rendering a timely and accurate diagnosis essential. This study introduces an innovative computer-aided diagnostic system employing a four-stage methodology—preprocessing, segmentation, feature extraction, and model training—to enhance early detection. The dataset undergoes cleansing during preprocessing to ensure high-quality input, and the ACT is employed for segmentation. They employ the GLCM approach to capture significant visual characteristics of lesions. They introduce a paradigm for semantic modelling, termed CNRNN, to use the optimal characteristics of both recurrent and convolutional neural networks. This framework supports two models that improve performance in phrase matching and classification: an attention-based response selection model and a novel model. The proposed system surpasses existing models with an accuracy of 96.28 percent. These results underscore the potential of employing DL techniques for the early detection of skin cancer, offering a powerful tool to assist in clinical decision-making and improve patient outcomes through expedited and more accurate diagnoses.

Keywords—Active Contour Technique (ACT), Grey Level Co-occurrence Matrix (GLCM), Natural Language Preprocessing (NLP), Computer Aided Diagnosis (CAD).

I. INTRODUCTION

Early detection is therefore paramount in the treatment of skin cancer. When diagnosing skin cancer doctors typically employ the biopsy technique. This process involves taking a small piece of skin from a suspicious area in order to diagnose cancer. It takes a long time is painful and moves at a snail's pace. Skin cancer signs can now be quickly and easily diagnosed using computer-based technology it's also more comfortable and cheaper than ever before. Several noninvasive methods are suggested for determining if skin cancer signs are indicative of skin cancer. Among the many cancers that have been diagnosed in the skin cancer ranks high. Given that the skin cancer is the biggest organ in the body, it is reasonable to consider skin cancer to be the most prevalent kind of cancer in humans [1]. In terms of classification melanoma and non-melanoma skin cancer are the two main

groups. A dangerous extremely rare and fatal form of skin cancer is melanoma. Although it accounts for of all skin cancer occurrences melanoma is responsible for a significantly higher mortality rate. As a general rule people may diagnose skin cancer on their own. But there are obstacles to early identification such as a lack of public knowledge, interest and ability to do SSE an absence of training to identify worrisome lesions and a failure to appreciate the significance of early medical presentation and there aren't any good plans to deal with these issues. A human malignancy that develops from defective cells is known as skin cancer [2]. Without prompt diagnosis it can metastasize to other areas of the body. It performed a study on melanoma. This was one of the earliest efforts to concentrate on Computer Aided Diagnosis (CAD) through the use of automated approaches for early skin lesion detection. Image analysis with an emphasis on color form and structure was the authors stated goal. Given that the lesion area has been appropriately segmented which seeks to isolate the lesion from the surrounding image [3].

The correct extraction of features in the subsequent steps depends on this. Without early detection and treatment, melanoma the most fatal kind of skin cancer can metastasize spread to other regions of the body and ultimately cause death. The rule identifies asymmetries border irregularities multi-coloring and dermoscopic structure as common markers of cancer. The skin has many important functions it prevents outside invaders and germs from penetrating the body, it aids in maintaining a constant internal temperature, and it allows us to feel touch, heat and cold [4]. A skin lesion is an abnormality in the skin that is noticeable in comparison to other areas of the skin. An infection either internal or external to the skin is the most fundamental and common reason for skin lesions. Skin cancer can be detected in a variety of ways visual examination by dermatologists or general practitioners and conventional methods of skin cancer detection such biopsy has various limitations and difficulties. BIOPSY is an invasive technique for illness detection it takes a long time is uncomfortable and could spread the disease [5]. Although a biopsy is necessary for a conclusive diagnosis when a suspicious sign it can be costly painful for the patient and lead to infection. Another way that doctors can

utilize their eyes and experience to detect skin cancer is with the naked. When doing a visual assessment, the healthcare provider's knowledge and personal judgment are crucial.

The remainder of the paper is structured as follows. In Section 2, they provide a concise overview of the pertinent literature. Section 3 introduces the CNRNN model. Section 4 delineates experimental findings derived from comprehensive datasets and applications. In conclusion, the finalize the paper in Section 5.

II. LITERATURE SURVEY

In order to skin cancer from spreading detection at an early stage is crucial. Melanoma basal cell carcinoma and squalors cell carcinoma are the three most dangerous forms of skin cancer among others. Skin cancer classification using an ANN classifier is explored in another study. The ANN success rate in skin cancer classification was achieved by a study that used SVM and KNN classifiers. In skin disease as in many other medical fields AI is finding widespread use [6]. The ML is a branch of AI that uses algorithms and statistical models to learn from data and then use that knowledge to predict the features of fresh samples and complete tasks. Skin Diseases is not as widely accepted as radiology when it comes to AI despite its important role in skin cancer detection [7]. The general public will soon have access to AI due to its increasing prevalence widespread use and new technological developments. The early detection of skin cancer is one area where AI could be useful. In skin disease, as in many other medical fields AI is finding widespread use. A branch of AI and ML makes use of statistical models and algorithms to learn from data in order to anticipate the properties of future samples and carry out a desired activity [8]. Skin cancer is not as widely accepted as radiology when it comes to AI despite its important role in skin cancer detection. The general public will soon have access to AI due to its increasing prevalence widespread use and new technological developments.

The early detection of skin cancer is one area where AI could be useful. A specific kind of ML known as DL makes use of stacked networks of DNN nodes that can learn and identify unique dataset properties. Computer models inspired by the architecture and functioning of real NN are known as ANN. In ANN the FFNN is the simplest kind. This research introduces a powerful diagnostic system that makes use of image processing methods and SVM algorithms [9]. It takes a picture of the damaged skin and run it through a number of pre-processing steps to create a better smoother version of the original. The picture is subsequently subjected to segmentation using thresholding and morphological techniques [10]. It takes skin pictures and pulls out some key characteristics including texture, colour and shape. The features of the texture are extracted using the GLCM technique. The features of colour, shape and extracted GLCM are fed into the SVM classifier. This system uses dull razor and quick median filtering techniques to preprocess the input dermoscopy images. Then the Maximum entropy threshold approach is used to segment the preprocessed images. Performing feature extraction using GLCM algorithms on

the segmented image [11]. Then a classification task was assigned to an ANN. Because of its efficacy and low complexity in producing an accurate model SVM have been extensively utilized by researchers. On the other hand ANN classifiers outperformed KNN classifiers in because they iteratively adjust connection weights by minimizing the error between the ground truth and the predicted outputs making them more accurate overall. Still cancer detection systems that use DL are the entire trend here. An ANN method utilizing a BPNN and an auto-associative NN was suggested by the authors in [12]. A standard-based approach to coetaneous malignant growth detection was suggested by [13]. Because these cancer cells must be found by hand treatment typically takes a long time. Using methods from machine ML a synthetic skin cancer detection system.

The primary contributions of this study can be encapsulated as follows: Their proposed hybrid CNRNN framework improves the framework's classification and matching capabilities by combining the best features of convolutional and recurrent neural networks to process text. This architecture allows the framework to seamlessly extract linguistic information from both sources. To identify skin cancer, it offers a novel framework and enhance the underlying CNRNN.

III. PROPOSED SYSTEM

The incidence of skin cancer is on the rise globally, with a particularly alarming trend in India. Since melanoma can be effectively treated with early skin cancer identification, the key to melanoma curability and survival is eliminating the cancer when it is in its early stages. One of the most common cancers in India today is malignant melanoma, which has been on the rise in recent decades. Automatic diagnosis can improve melanoma detection accuracy because clinical findings aren't always reliable.

These 2357 photos were compiled from The International Skin Imaging Collaboration (ISIC) and depict many types of cancer, both benign and malignant. With the exception of melanomas and moles, whose images are significantly more prominent, all photographs were sorted according to the ISIC categorisation, and each subgroup was divided into an equal number of images [14].

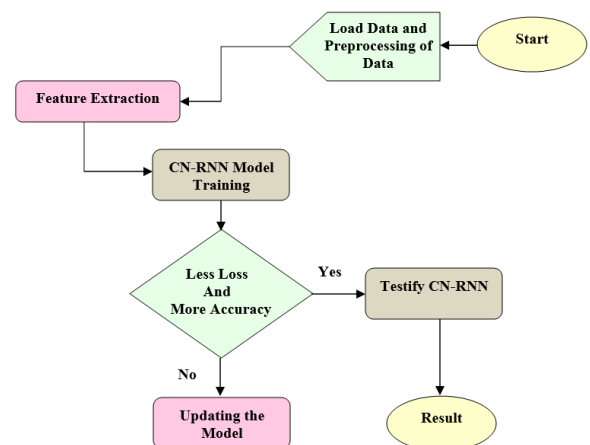


Fig. 1. Skin Cancer Detection using CNRNN

A CNRNN relies on a set of weights optimised for specific tasks, such as picture segmentation, and a number of 2D matrices is shown in Figure 1 [15].

A. Preprocessing:

In order to get the improved image, the original image must first undergo image processing, which is known as pre-processing. Common actions in the pre-processing step include resizing photos to lower quality pixels in order to reduce processing time. A binary mask is used to create a fresh image that is free of the bright area surrounding the lesion [16]. To remove unnecessary portions, this image has been trimmed. The next stage involves removing the hairs through screening. Finally, the original RGB photographs are transformed into intensity greyscale to mitigate the effects of varying skin tones and to enhance the suppression of significant oscillations within the lesion and background.

B. Segmentation:

An essential part of picture processing is segmentation. They can use it to extract a specific area of the image and work with it separately [17]. Segmentation is crucial in image analysis since it enables the processing methods for subsequent phases. When analysing medical photos, segmentation is a must. The success of the segmentation process determines the efficiency and accuracy of the following image processing processes. Segmenting images into their respective regions of interest is essential for medical image analysis. If the segmentation procedure is done correctly, the interest pixels will yield the right results. Image segmentation can be accomplished using a variety of methods and algorithms. An effective method for analysing medical images, the ACT was utilised for picture segmentation in the suggested system. By separating the affected area from the surrounding healthy skin, this method can identify the skin lesion. Accurate feature extraction relies on a segmentation procedure that is efficient.

C. Feature Extraction:

In order to retrieve data from a specific picture, feature extraction is crucial. In this case, they are analysing texture images using GLCM. The spatial dependency between image pixels can be captured using GLCM [18]. The most frequent features, including contrast, mean, energy, and homogeneity, can be captured by GLCM using a grey level picture matrix in Equation (1) – (4).

Energy:

$$\sum_k \sum_l A^s(k, l) \quad (1)$$

Contrast:

$$\sum_k \sum_l (k - l)^2 A(k, l) \quad (2)$$

Mean (ρ):

$$\frac{\sum_k \sum_l A(k, l)}{O * P} \quad (3)$$

Homogeneity:

$$\sum_k \sum_l \frac{A(k, l)}{1 + |k - l|} \quad (4)$$

Feature extraction is a method for classifying images from a larger set of inputs by removing irrelevant values or features from the original image data collection.

D. Model Training:

1) Framework for Hybrid:

Encoding a text sequence as an vector embedding using models such as CNRNN has become the norm for sequence modelling due to the recent breakthroughs in neural network models in NLP. Encoding each sequence as a vector and subsequently amalgamating them to facilitate a selection is a straightforward method for matching sequences. There is typically a significant size disparity between the input and filter sizes in a CNN [19]. Because of this, the output typically highlights the local n -gram lexical linkages and is only interactive with a small subset of the input. However, RNN works great when it comes to modelling sequences. In particular, LSTM models are able to effectively retain the valuable information derived from long-range dependencies, but at the cost of disregarding the local n -gram coherence. In essence, there are advantages and disadvantages to both CNRNN. It has been discovered that encoding a complete sequence with a CNRNN vector is insufficient to capture all the critical information in the sequence.

Several attempts have been made to create a hybrid framework that can efficiently combine CNRNN and reap the benefits of both. They created hybrid models that extract information linguistic from both structures to passage address by processing the text using CNRNN. In addition, unlike earlier approaches to sentence modelling that attempted to cram all phrase information into a vector. Furthermore, their similarity focuses layer and paired word interaction model fine-grained capture semantic information better than previous approaches to sentence modelling that tried to pack all information phrase into a fixed length of vector. By combining a quick deep model with an initial model retrieval of data, it presents a hybrid model that efficiently manages AS.

2) CNRNN:

CNN for semantic representations in skin cancer modelling and other NLP applications, a combination of convolutional and layers of nonlinear, followed by a layer for pooling, has shown to outperform more conventional approaches. But CNN is good at focussing on local n -gram features, therefore it missed out on long-distance interactions.

Algorithm 1: CNRNN Model

Input:	The sentence of input comprises a sequence of words: $[Z_1, \dots, Z_{ q }]$, where Z_k is selected from a finite vocabulary X .
1.	Utilise a search table operation $x_k = JR_Z(Z_k)$ to represent Z_k with its matching word embedding $x_k \in Q^{b_z}$. The input phrase embedding matrix,

	denoted as $T_z^b \times q $, is specified as $Q = [x_1, \dots, x_{ q }]$.
2.	To get the outputs $t_r^h, t_r^d \in T_t^b$ and the final hidden states $f_{ q }^h, f_{ q }^d$ of the forward and backward RNN at time step q , use BI-RNN to process Q . $t_r = [t_r^h, t_r^d]$ is the result of adding t_r^h, t_r^d to get $t_r \in T^{2b_t}$.
3.	A , where $A_{kr} = h_k^R \cdot t_r$, is obtained by processing T using a set of p filter vectors $h_k \in T^{2b_t}$.
4.	Put A through its paces with the ReLU function $\max(0, v)$ and expect results C defined as $C_{kt} = \max(0, A_{kr})$.
5.	Maximise the pooling operation to process C and obtain $V_q \in T^p$, where $V_q[k] = \max(0, C[k, :])$.
Output:	Return V_q

In contrast, RNNs are able to concurrently emphasise local information at each time step q while efficiently preserving relevant information from long-range depends. It has been discovered that encoding a complete sequence with a vector from either CNRNN is insufficient to capture all the critical sequence from the information. CNRNN fundamentally have their own advantages and disadvantages. They present the CNRNN hybrid architecture, which combines CNNs and RNNs in a consistent manner, so that can reap the benefits of both. There are a total of four layers in our model: word embedding, BI-RNN, convolutional, and max-pooling. This is where providing a brief overview of CNRNN in Algorithm 1 and delve into detail:

a) Layer of Word Embeddings:

The input original is a sentence Q composed of a sequence of words: $[z_1, \dots, z_{|q|}]$, where each word is selected from a vocabulary finite X of size $|X|$. With the word embedding matrix $Z \in T^{b_z \times |X|}$ and the word embedding dimension b_z each word is transformed into a dense vector low-dimensional $x_k = JR_Z(z_k)$ before moving on to the next layer. Each embedding word in the sentence input Q is denoted by a column in a matrix.

b) Layer of Bi-RNN:

The BI-RNN layer, which has a dimension b_t , is then fed the sentence matrix. Only one way Not using the information contextual from the future words causes RNN to be inefficient. By analysing the sequence in both the backward and forward directions, the Bidirectional RNN makes use of both past and future contexts. The output t_r is the sum of the two vectors output t_r^h and t_r^d in both directions at each time step r . Additionally, complete sentences are typically represented by the final concealed states $f_{|q|}^h, f_{|q|}^d$ from both directions. They implement an AM for AS utilising $f_{|q|}^h, f_{|q|}^d$.

c) Layer of Convolutional:

Using a collection of p filter vectors $h_k \in T^{2ob_t}$ with a sliding window size o , the layer of convolution processes the output of the BI-RNN layer, $T \in T^{|q| \times 2b_t}$, through a operation of linear convolution. In formal terms, they can say that $T_{k:k+l}$ is the sum of $t_k, t_{k+1}, \dots, t_{k+l}$. The following equation (5) shows how the convolution linear process takes the product dot of h_k with each m -gram in the sentence Q :

$$A_{kr} = h_k^R \cdot T_{r-0+1:r} \quad (5)$$

Specifically, the layer of BI-RNN is already capable of adaptively capturing dependencies on different time scales, hence the breadth of filter o maps in CNRNN is set to 1. Hence, a potential bottleneck of CNN can be avoided by not imposing a fixed size on the sliding window. Equation (6) shows the simplified convolution operation.

$$A_{kr} = h_k^R \cdot t_r \quad (6)$$

Where $A \in T^{p \times |q|}$. Using a function of non-linear activation to process A allows for the learning of non-decision linear boundaries. As the function non-linear activation, they utilised a ReLU function in this research.

d) Layer of Pooling:

To extract robust features from the output of convolutional operations, pooling techniques such as min-pooling, max-pooling, and average-pooling are frequently used. In order to capture the most signal significant, they suggest in this study max-pooling applying for each filter. To create the representation final vector $V_q \in T^p$ for the sentence input Q , then formally extract the maximum value from each row of A .

IV. RESULT AND DISCUSSION

Skin cancer is the leading cause of death for people in the modern world. Skin cancer is the result of aberrant skin cell proliferation, which can happen anywhere on the body but most frequently occurs on areas exposed to sunlight. In their early stages, the majority of skin cancers are treatable. Therefore, a patient's life may be saved by an early and prompt diagnosis of skin cancer. Skin cancer can now be detected early in its early stages due to modern technology.

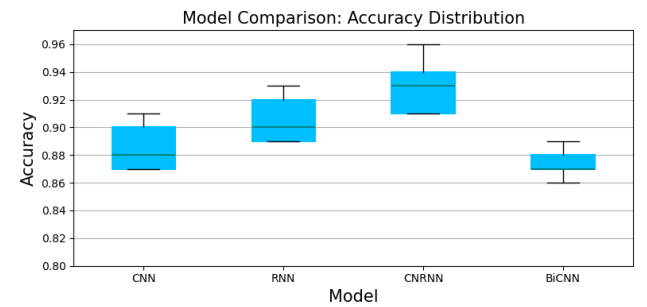


Fig. 2. Different Model Accuracy Comparison

Figure 2 shows that when they zero in on balanced accuracy, the outcomes are marginally poorer, even if the methods behave similarly to global accuracy. BiCNN is slightly different and produces less balanced accuracy. 89. The best result was a balanced accuracy of 64%, with CNRNN being the model that came close to this mark.

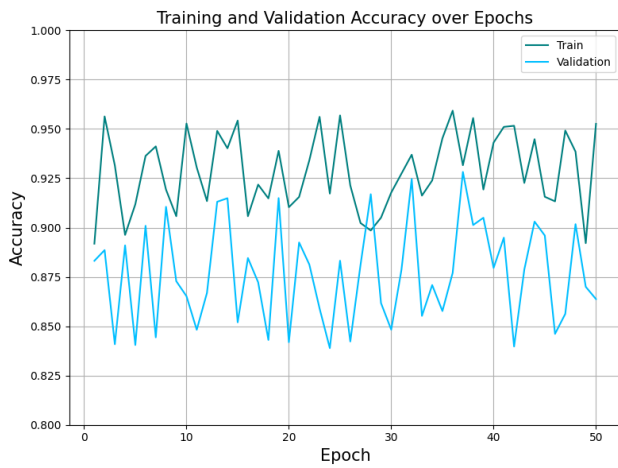


Fig. 3. Training and Validation Accuracy

The improved picture dataset trained and validated using CNRNN is displayed in Figure 3. The CNRNN-enhanced dataset maintains a consistent training accuracy of roughly 0.96, which is quite close to the original dataset.

TABLE I. THE CLASSIFIERS ACCURACY RESULT

Models	Accuracy		
	Training	Validation	Testing
CNN	0.9187	0.8643	0.8651
RNN	0.9352	0.8876	0.8892
CNRNN	0.9628	0.9061	0.9078
BiCNN	0.8964	0.8321	0.8343

Table 1 displays the results for each classifier, however. When it comes to the training set, CNRNN once again produces the greatest results in the classifier, with an accuracy of over 0.9628%.

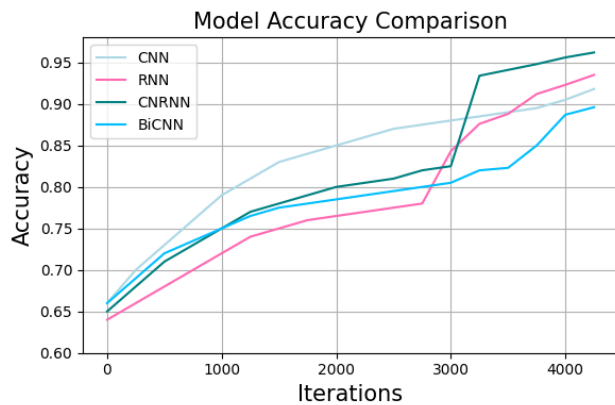


Fig. 4. Training Accuracy Comparison

Figure 4 shows the training curves used to fine-tune the four deep networks that were part of this study. Evidently, CNRNN is the most effective model, since it achieves the most accuracy.

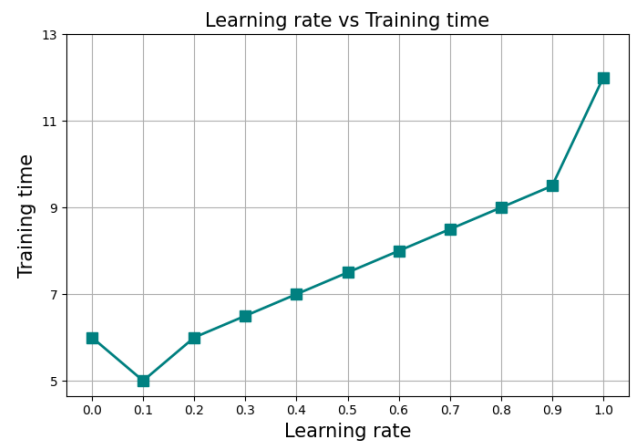


Fig. 5. The Proposed Model Learning and Training Time

Training duration and performance ratio are both affected by the learning rate, as seen in Figure 5.

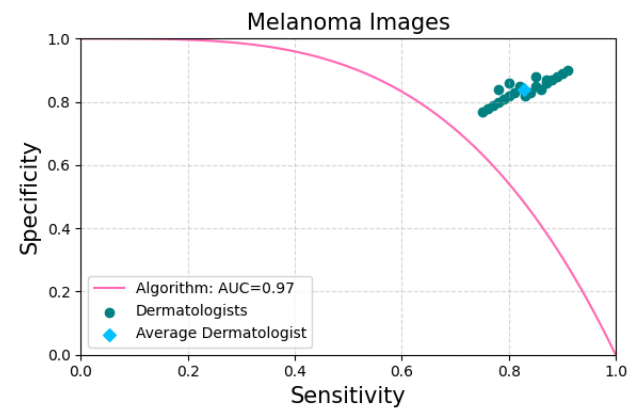


Fig. 6. AUC with Specificity and Sensitivity

Figure 6 in the Extended Data Set displays the outcomes of this investigation. The CNRNN beats the average and dermatologists in terms of sensitivity and specificity, as well as AUC.

V. CONCLUSION

The most prevalent type of cancer in people is skin cancer. This kind of cancer is lethal. The majority of skin malignancies can be cured in their early stages. Therefore, patients can be saved if skin cancer is detected early. The development of technology has made it feasible to identify skin cancer early. The type of cancer that affects the skin is called skin cancer. Skin cancer can manifest as either benign or malignant. Simply said, benign melanoma is the appearance of skin moles. When bleeding sores occur, it is known as malignant melanoma. Cancerous The deadliest type of skin cancer is melanoma. It results from the growth of cancer in a pigmented skin lesion. The dataset will be cleansed during preprocessing. The segmentation process makes use of the ACT. The GLCM technique must be used to extract certain visual features. In this work, it presents a generic inference hybrid framework for CNRNN of semantic modelling of skin cancer. This framework strengthens the new framework's semantic understanding capabilities by seamlessly integrating the advantages of extracting various linguistic information from both

convolutional and RNN structures. In comparison to the other models, the accuracy of the proposed CNRNN model is 96.28%.

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