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Research Article

A Novel Segmentation Based Technique for Detection of Skin Lesion using Deep Learning

[1]Nikhil Singh*, [2]Sachin Kumar, [3]Shriram K. Vasudevan

[1,2]Amity School of Engineering and Technology (ASET), Lucknow, UP, India

[3]Lead-Technology (Evangelist) Intel Corporation Bengaluru, India

nikhil26194@gmail.com, skumar3@lko.amity.edu, shriramkv@gmail.com

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ABSTRACT

Skin cancer is a common and serious disease in modern times. Early detection of skin cancer is crucial for reducing mortality rates. Due to the rapid increase in skin cancer cases, there is a sudden need to develop a Computer-Aided Diagnosis (CAD) framework that can accurately diagnose skin lesions. CAD models may aid doctors in identifying problems, resulting in improved diagnostic outcomes. Our analysis has shown that the Deep Neural Network exhibits higher accuracy compared to other machine learning methods included in the research. This paper presents a new method for categorizing skin lesions. The method includes pre-processing, bilateral filtering approaches, segmentation, ResNet-50 feature extraction, and feature selection utilizing the Whale Optimization Method (WOA) algorithm. The DBN model achieved the maximum accuracy of 96.1% in the suggested system. The suggested research aids in the early detection of seven types of skin cancer, allowing for validation and suitable treatment by medical professionals.

Keywords: Skin Lesion, Computer-Aided Diagnosis, Segmentation, Feature Extraction, Deep Learning

1. INTRODUCTION

The skin, being one of the largest and most delicate organs in the human body, is susceptible to a range of illnesses. Many of these illnesses present unfamiliar symptoms, which complicates the accurate diagnosis for dermatologists [1]. Technology has revolutionized all aspects of contemporary life, including the medical sector. Several effective health care systems have been established for patients and healthcare providers. These systems encompass everything from the enrollment process to utilizing technology for detecting illnesses.

The skin, the largest and most vital organ of the body, is crucial for maintaining health. The skin of an individual covers around 22 square feet of the body's entire outermost layer [2]. The human body's outer layer has multiple functions such as resistance against external dangers, protection from pathogens and components, and regulation of the internal temperature and feelings of heat and cold. Various internal and environmental elements, together with the skin itself, might influence the situation. Humans are susceptible to infections caused by viruses, fungal infections, and allergic reactions.

The absence of general knowledge of the dangers of sunlight has been linked to higher rates of skin cancer. Only a biopsy can determine whether or not we are at a greater risk of acquiring a skin illness. An assessment of the hand is conducted, taking into account several histological characteristics. A manual biopsy procedure increases the likelihood of errors and delays in obtaining findings. Physicians find it challenging to pinpoint certain skin diseases and determine their severity during this stage of the diagnostic procedure.

1.1 Screening for Skin Lesion Cancer

Screening for skin lesion cancer typically involves a few different methods [3]:

i. **Self-Examination:** Regularly examining your own skin can help detect any changes or abnormalities. Look for new moles, changes in existing moles, or any other unusual marks or growths.
ii. **Clinical Examination:** During routine check-ups with a healthcare provider, they may perform a thorough examination of your skin, including areas that are difficult for you to see on your own.
iii. **Dermoscopy:** This involves using a special magnifying instrument called a dermoscope to examine skin lesions more closely. Dermoscopy can help identify features that might suggest skin cancer.
iv. **Biopsy:** If a problematic lesion is detected, a biopsy could be conducted. A biopsy involves extracting a minute tissue specimen from the lesion and scrutinizing it under a microscope to ascertain the presence of cancerous cells.
v. **Imaging tests:** Imaging procedures, such as ultrasonography, CT scans, or MRI examinations, may be utilized to further assess worrisome lesions, particularly if there is apprehension over the possible spread of the disease to other areas of the body.

It's important to note that while these methods can help detect skin cancer, they are not foolproof. Periodic exams and timely discovery may significantly enhance the likelihood of effective therapy. If you see any alterations in the surface of your skin or have apprehensions about a specific lesion, it's important to see a healthcare provider for evaluation [4].

1.2 Types of Skin Cancer

Some of the most prevalent forms of skin cancer, out of many others, are [5]:

i. Basal Cell Carcinoma (BCC):

Basal cell carcinoma constitutes the predominant form of skin cancer. It often manifests as a flesh-colored, pearly lump or a pinkish area of skin. It often occurs on sun-exposed parts of the skin, including the area around the ears, neck region, forehead, shoulders, and rear. Basal cell carcinoma (BCC) often has a sluggish growth rate and is usually less aggressive compared to other forms of skin cancer. However, if ignored, it may still lead to local tissue damage..

ii. Squamous Cell Carcinoma (SCC):

The next most prevalent kind of tumor on the skin is squamous cell carcinoma. It often manifests as a raised hump with a crusted surface or a red, scaly area. Squamous cell carcinoma, similar to basal cell carcinoma, often develops on skin that has been exposed to the sun. Squamous cell carcinoma is more likely to propagate to other areas of the human body and may develop faster than basal cell carcinoma, when not treated soon.

iii. Melanoma:

Compared to squamous cell carcinoma and basal cell carcinoma, melanoma tends to be less prevalent; nonetheless, it is more malignant and, if left untreated, may be fatal. Melanocytes, the skin-coloring pigmentation cells, are the usual incubators for melanoma. A new pigmentation growth or an abnormal mole are common symptoms of melanoma. It is not limited to sun-exposed regions; it may manifest anytime on the body. The ability of melanoma to advance to other areas of the body makes early discovery of the cancer critical for effective therapy.

All three types of skin lesion can be shown in figure 1.

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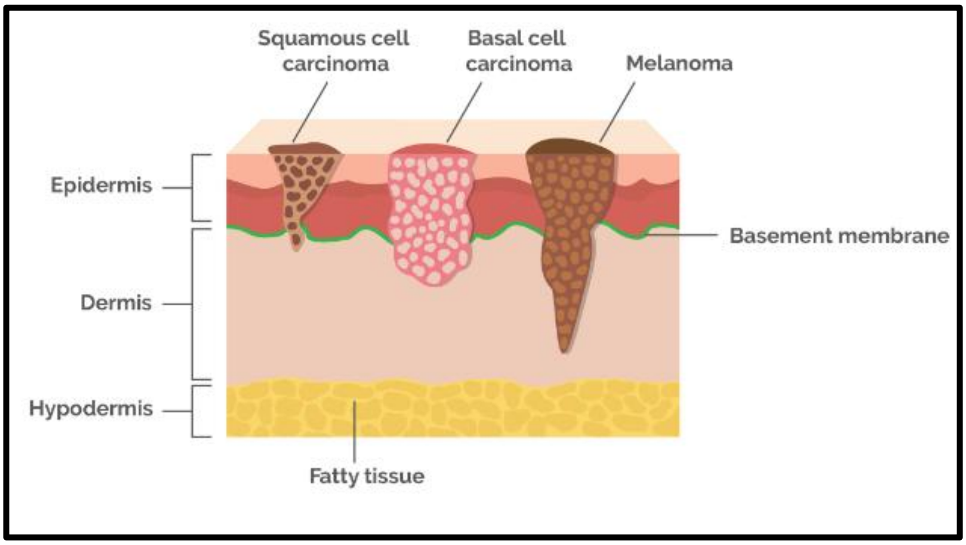

Figure 1: Types of Skin Cancer [6]

1.3 Skin Cancer Detection using Artificial Intelligence Techniques

Deep learning within artificial intelligence has the capability of autonomously obtaining features from large amounts of data. Data can be extracted from photos that are imperceptible to the naked eye. Early detection of tumors using imaging information is crucial. AI has been shown to be effective in diagnosing and treating tumors. A complex neural network architecture, including strong conceptual reasoning and learning capabilities, has the potential to closely emulate human cognition [7].

Artificial intelligence can swiftly and intuitively make rapid decisions to address problems, similar to the human brain. AI may significantly enhance cancer research models, and this conclusion is easily reached. AI-enabled Computer-Aided Diagnostics (CAD) are revolutionizing a growing amount of healthcare diagnostics. Enhanced in vivo examination of lesioned features and risk assessment can be achieved by dermoscopy or, less frequently, confocal microscopy. Algorithms used by AI in healthcare imaging have demonstrated equal or superior efficiency to clinicians in identifying illnesses. Recently, deep learning has developed many end-to-end solutions for detecting anomalies including breast or brain cancers, lung or stomach malignancies, skin blemishes, or foot issues.

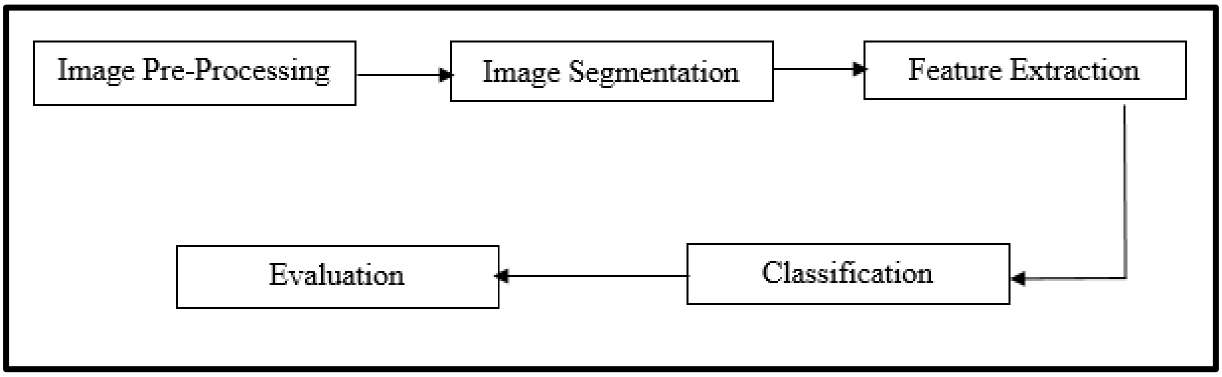

Figure 2: AI-enabled Computer-Aided Diagnostics (CAD) for predicting cancer

Artificial intelligence is becoming more prevalent in the field of health. Dermatologists and dermatopathologists ought to work together with AI experts to use the technology, despite their initial reservations. It has a chance to greatly enhance our capacity to make well-informed health decisions and broaden access to healthcare services.

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Research Article

1.4 Methods for Detecting Skin Cancer Using Machine Learning and Deep Learning

AI is a field of computer science that utilizes technology and systems to enhance human intellect. In recent decades, software engineers have created specific techniques for systems that process data. Thus, the use of heuristics in human decision-making within the clinical sector is deemed impractical for clear guidelines [8]. Recently, machine learning has garnered significant attention from developers for its use in everyday life, such as personalized online movie and image recommendations and self-driving automobiles. Despite being controversial, machine learning is quite pertinent to traditional methods in the majority of dermatological examinations.

Skin cancer detection primarily depends on deep neural systems. Their framework is based on nodes that are linked together. Their neuronal connectivity structure is similar to that of the human brain. Their nodes collaborate to address particular problems. Neural networks are taught for certain tasks and can execute them proficiently. We created neural networks for image recognition to distinguish various types of skin tumors based on their characteristics as part of our study.

An artificial neural network is characterized by its use of nonlinear and probabilistic modeling. The design is modeled from the fundamental structure of the human brain. An artificial neural network (ANN) consists of three groups of neurons, each serving a unique function. The initial layer consists of neurons that function as "inputs," transmitting data to the second layer, known as the "intermediate" layer of the brain. Hidden layers are the intermediary layers of a neural network. A standard artificial neural network may consist of multiple layers. The third tier of output neurons obtains information from intermediary neurons. Backpropagation is used at each layer to understand the complex links between input and output layers. It closely resembles a neural network. The phrases "neural network" and "artificial neural network" are frequently used interchangeably in the field of computer science.

Deep Learning is used in skin cancer identification systems to categorize extracted features [9]. Once the training set has been educated and categorized, input photos are classed as either melanoma or non-melanoma. The number of input photos dictates the quantity of hidden layers in Neural Network (NN). The input dataset links the initial layer of the neural network to the hidden layer. An unlabeled dataset can be processed using either supervised or unsupervised learning techniques, depending on whether the dataset has labels. Weights in a neural network are acquired through backpropagation or feedforward design. Both approaches process the fundamental dataset in different ways. Feed-forward neuronal networks can only transmit data in a unidirectional manner. Only information from the input layer to the output layer is transmitted.

1.5 Motivation

At this time, skin cancer ranks first among all diseases, both in terms of frequency and severity. Although it is rare, malignant melanoma has the greatest death rate of all skin cancers. The removal of the lesion is the treatment of choice for Malignant Melanoma if caught early enough. But the risk of mortality rises in the event that the diagnosis is postponed. In the last few decades, a CAD-based automated method for skin lesion classification has been developed. When doctors aren't well-versed in a certain area, these modules might help them make better selections. The widespread adoption of semi-or fully-automated models for diagnostics was anticipated.

Skin lesion classification in CAD systems relies on picture pre-processing, noise elimination, lesion segmentation, feature extraction from the lesion region, and lesion classification using typical Machine Learning methods [10]. Recently, advanced segmentation methods have been introduced using supervised machine learning techniques. Introducing a precise skin lesion segmentation module is difficult due to low contrast between the lesion and backdrop, irregular border shapes, fuzzy edges, and fragmentation. Neural Networks (NN) have demonstrated exceptional performance in conducting numerous clinical classifications. NN-related methods have been predominantly utilized for skin lesion classification, outperforming other methodologies. Enormous NN-related algorithms have been used for skin lesion classification without prior image segmentation, unlike traditional approaches. Although

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Research Article

NN-based approaches have shown excellent classification performance in skin lesion classification without lesion segmentation techniques, the full potential of skin lesion segmentation on NN-based classifiers has not been achieved. A study has only partially utilized lesion segmentation information in a NN-based classification process to improve model performance.

1.6: Objective of Research

This would be helpful to the medical professionals in making an early diagnosis and classifying the lesions. The primary purpose of this study.

- Data preprocessing and numerical findings from the HAM10000 and ISIC2019 datasets demonstrate that the proposed framework outperforms current leading approaches in terms of efficiency and accuracy.
- Provide a new technique for segmenting skin images by utilizing Bilateral Filtering, clustering algorithm and Feature extraction techniques.
- To assess the parameters needed for classification and evaluation using different machine learning and deep learning classifiers.

This section offers a thorough overview of skin types, lesion basics, imaging techniques, and Artificial Intelligence. The following section will analyse the prior researchers' attempts to detect skin cancer in digital photos.

2. LITERATURE SURVEY

The preceding section has completed a fundamental review of the skin lesion, Artificial Intelligence, Machine Learning and Deep Learning ideas. This section aims to conduct a comprehensive examination of several computer-aided design (CAD) models that have been documented in the literature for the purpose of diagnosing and classifying skin lesions using dermoscopic pictures [11]. Initially we covered, a comprehensive examination of the segmentation approaches devised for the purpose of identifying skin lesions has been conducted. Furthermore, this study examines a collection of skin lesion classification models that specifically make use of ISIC datasets [12].

Debelee, T. G. (2023) examined established segmentation algorithms, encompassing deep-learning-based, graph-based, and region-based approaches. This text discusses the specific challenges, datasets, as well as assessment criteria that are relevant to the task of segmenting skin lesions. The survey extensively covers significant datasets, benchmark issues, and assessment metrics that are pertinent to the assessment of skin lesions. This provides a thorough and inclusive summary of the topic. The report concludes by providing a summary of the significant patterns, difficulties, and potential future paths in the categorization, segmentation, and detection of skin lesions. The intention is to encourage further progress in this crucial field of dermatological study.

Akram, A. et al. (2023) employed a deep learning framework that is hybrid that integrates two state-of-the-art techniques: Mask Region-based Convolutional Neural Network (MRCNN) for conceptual segmentation and ResNet50 for lesion identification. The MRCNN is employed to accurately determine the exact position of a skin lesion by delineating its borders. We gather an extensive and meticulously annotated assortment of dermoscopy photos to train our models comprehensively. The dataset is used to train a hybrid deep learning model that captures nuanced representations of the images, from beginning to end. The empirical findings utilizing dermoscopy images demonstrate that the proposed hybrid approach surpasses the existing cutting-edge approaches. Furthermore, the categorization of skin lesions exhibits exceptional precision and reliability, representing a significant improvement compared to conventional approaches. The model undergoes rigorous testing on the ISIC 2020 Challenge dataset, achieving an impressive accuracy of 96.75%. Segmentation and classification algorithms provide outstanding performance when compared to the current standards in IoMT.

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Research Article

Hameed, A. et al. (2023) suggested various approach in the field of Dermatology for classifying pigmented lesions. Researchers are studying the binary classification problem of distinguishing Melanocytic lesions from typical ones. This study utilizes HAM10000 dataset provided by the International Skin Image Collaboration. The dataset comprises seven categories of skin cancer ailments. In addition, our research demonstrates the superiority of our stacked CNN method, which achieves an accuracy of 95.2% through the utilization of data augmentation and picture preprocessing approaches.

Sulthana, R et al. (2024) used HAM10000 dataset, comprising 10000 dermatoscopic pictures representing several demographics, was utilized. If you want to use this dataset, you may do so for free via the ISIC Library. Before being used for modeling, the picture data was pre-processed. In order to better understand the dataset and its many features, we ran an exploratory data analysis (EDA). For image segmentation and feature extraction, an adjusted Gaussian filtering method and SFTA were used. The S-MobileNet model was then fed the prepared dataset. Furthermore, a different technique was employed to compress the layers in the S-MobileNet design, ensuring a model that is both lightweight and high-performing.

The framework was trained via a series of trials and its efficacy was assessed using several metrics. Our research findings demonstrate that the model's performance is enhanced with the use of a pre-processing technique. Furthermore, the reduced S-MobileNet exhibited higher precision for classification in comparison to S-MobileNet.

This section explores multiple segmentation and classification strategies to achieve precise diagnosis and define lesions using deep learning approaches. In the following section, we will explore a distinctive hybrid method that can be employed to detect lesions using dermoscopy images.

3. METHODOLOGY

The skin, being a vital and expansive organ, is susceptible to the transmission of various forms of bacteria, viruses, and inflammatory disorders, leading to potentially life-threatening illnesses. Several examples of skin diseases include acne, atopic dermatitis, and others. The skin illness can only be effectively treated if it is diagnosed in the early stage. Several recovery models exist, with one notable example being "Dermoscop" [17-18]. This method is commonly employed by clinicians to analyse alterations in the skin surface. It involves the use of a strong light and polarization techniques to minimize surface reflection. A vast multitude of individuals worldwide are impacted by various forms of dermatological conditions. Melanoma is a highly alarming skin condition in comparison to other illnesses. Previous examinations aid in mitigating the dissemination of diseases throughout the skin. Skin types differ among individuals and can be classified as either main or secondary.

The primary objective of segmentation is to separate individuals from sample images, whereas in the detection phase, irregularities are identified in an image based on its properties. Ultimately, recognition is executed to extract multi-level characteristics and classify them utilizing deep learning methodologies.

This study introduces a novel deep learning-based computer-aided design (CAD) technique, referred to as the model, for the purpose of skin lesion classification and detection. The diagnostic model utilised in this study encompasses a sequence of procedures, specifically preliminary processing, segmentation, extraction of features, and classification, as depicted in Figure 2.

3.1 Dataset Collection

A large number of dermoscopy pictures have been collected and made accessible by the International Skin Imaging Collaboration (ISIC). This dataset comprises over 20,000 photographs obtained from renowned clinical centers worldwide. These images were captured utilizing a diverse range of devices that were accessible at each institution. The ISIC dataset was initially accessible for a public assessment contest in 2016. The challenge aimed to provide a dataset that would stimulate the advancement of

Journal of Information Systems Engineering and Management
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Research Article

computational methods for the segmentation, identification of dermoscopic features, and classification of melanoma. In 2017, the ISIC hosted the second round of the challenge, which featured a more extensive dataset. The expanded dataset comprises 2,000 images intended for training, accompanied by filters for segmentation, superpixel filters for dermoscopic feature extraction, including annotation for classification.

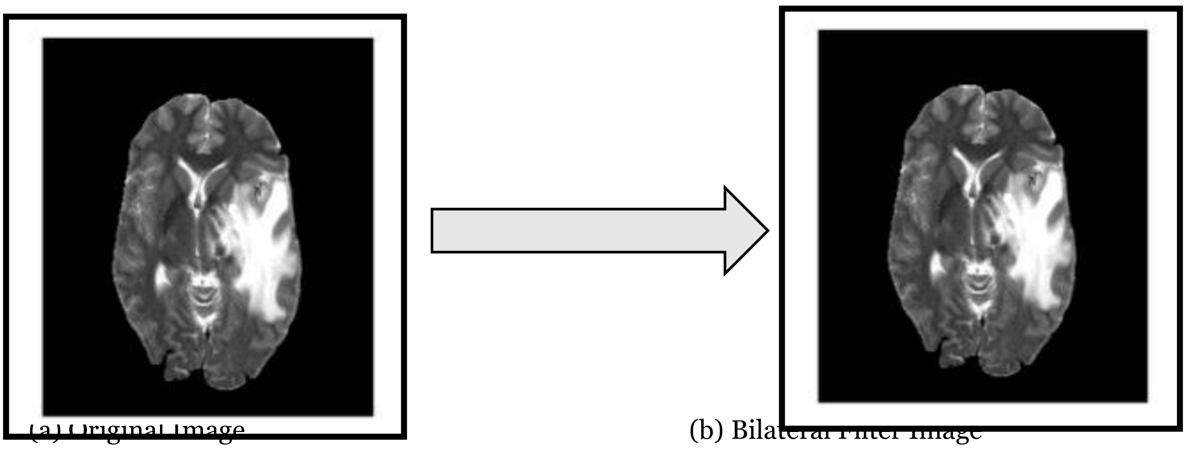
The present research analyzed two distinct skin lesion cancer datasets, both of which are available at the UCI Machine Learning Repository. Dataset 1, also known as ISIC, contains 379 cases and 34 features. On the other hand, Dataset 2, known as HAM10000 or ISIC 2018, consists of 286 occurrences and 9 features [19]. To normalize the information we have, we employ many pre-processing stages, including data attribution, data scaling, and standardization [1] [12]. These phases aim to enhance the accuracy of the classification of the framework.

3.2 Filtering for Smoothing Image (CB)

In order to achieve image smoothing while preserving the integrity of edges and reducing noise, one can employ a nonlinear, bilateral filter. By employing a weighted average of the intensity values of adjacent pixels, the process involves substituting the intensity value of each pixel [20]. The bilateral filter is a nonlinear approach utilised to induce image blurring while preserving distinct edges. The universal use of this technique in digital photography applications, such as colour mapping, style transfer, relighting, and denoising, can be attributed to its capability to decompose a picture into distinct scales without creating haloes after alteration.

$$F[I]_p = \frac{1}{N_p}\sum G_{\sigma_s}(p-q)\sum G_{\sigma_r}\left(I_p - I_q\right)I_q \tag{1}$$

In this equation, the normalisation factor N_p and the variation in weight are introduced as additional terms. The value σ_s reflects the geographic reach of the kernel, which corresponds to the dimensions of the neighbourhood. Conversely, σ_r denotes the minimum magnitude of an edge's value. The method ensures that only pixels with intensity levels similar to those of the center pixel are considered for distortion, while yet maintaining clear variations in intensity. A lower value of σ_r correlates to a more defined edge. As the value of σ approaches endlessly, the equation demonstrates a Gaussian blurring.



(a) Original Image (b) Bilateral Filter Image

Figure 3: Transformation of Original Image to Bilateral Filter Image

The input for the BF for pre-processing is depicted in Figure 3 (a). Bilateral Filter effectively eliminates the majority of roughness, noise, and intricate features, while maintaining prominent sharp edges without any blurring, as depicted in Figure 3 (b).

3.3 Segmentation

Picture segmentation is a useful technique for extracting the specific region of interest included inside a picture. Image decomposition is the act of dividing an image into its constituent parts. Image objects

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Research Article

are the constituent parts of an image. This is accomplished by analysing the characteristics of the image, such as its similarity and discontinuity, among other factors. Image segmentation aims to simplify the intricacy of an image, enabling more efficient analysis [21].

Our suggested segmentation technique for image classification is K-Means clustering algorithm is laid out in this portion of the section. K-means is a straightforward unsupervised learning method that solves the problem of grouping in a transparent manner. The method entails a straightforward and uncomplicated approach to organizing a set of given data into a particular number of clusters (assumed to be K clusters). The primary concept is to create a declaration of the meaning of words using K centroids, with each centroid representing a distinct group. These centroids must be strategically positioned due to different placements yield varied outcomes. Therefore, it is optimal to position them at the greatest possible distance from one another [22]. The subsequent procedure involves associating each data point with its corresponding properties and aggregating them to the closest centroid. Once there is no further delay, the initial stage is finished and an early group meeting is scheduled. At the moment, you need to figure out K novel centroids by averaging the cluster centers you got in the last phase. After K new centroids have been found, using the same computational abilities, a new link must be created among the data elements and the nearest new centroid. A circle has been created. The result of this process can be described as the gradual relocation of the K centroids until no further changes occur. Put simply, centroids no longer move. Finally, this procedure is designed to diminish the significance of a specific ultimate goal, which in this case is the utilization of a squared error group event.

The objective function is described as the total of the Euclidean distances between every instance of training and its corresponding cluster center, aggregated over all k clusters. We can express it in this manner in equation 2.

$$O = \sum_{i=1}^{k} \sum_{j=1}^{n} (y_i - c_j) \qquad (2)$$

Where k represents the number of clusters, and n represents the number of cases. Distance function calculated by subtracting the centroid of cluster j.

3.4 Feature Extraction

The acceleration in exploitation facilitates the identification of pertinent characteristics and mitigates the risk of overfitting issues. The input images undergo normalization and are then processed by the ResNet50 model to extract features [23] [24].

For feature extraction, we utilize a convolutional neural network named ResNet-50, which consists of 50 layers. The ImageNet database includes a pre-trained iteration of the network that has undergone training using over one million photographs. ResNet50 employs identity mapping, which enables the model to circumvent a weight layer of the neural network (NN) if the current layer is deemed unnecessary. Within the training set, the issue of overfitting is addressed, and the ResNet50 model is composed of 50 layers specifically designed for feature extraction. Once the feature extraction is finished, the process of choosing features is performed using the Whale Optimization Method (WOA) algorithm. The procedure of feature selection is considered a challenging task in worldwide combinatorial optimization (CO). Its goal is to maintain a consistent degree of accuracy during classification by minimizing the presence of noisy and duplicate information.

3.5 Classification Algorithm

After the extraction of a valuable set of feature vectors by the model, they are then utilized as input for the classification algorithms. The aforementioned models have the capability to ascertain and categorize various forms of skin cancer [25].

In this study, we assess the accuracy of four classifiers: Support Vector Machine (SVM), Convolutional Deep Neural Networks (CDNN), and Deep Belief Network (DBN) algorithms [27-28]. These classifiers

Journal of Information Systems Engineering and Management
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are chosen empirically from all known classifiers in the research based on their precision and consistency.

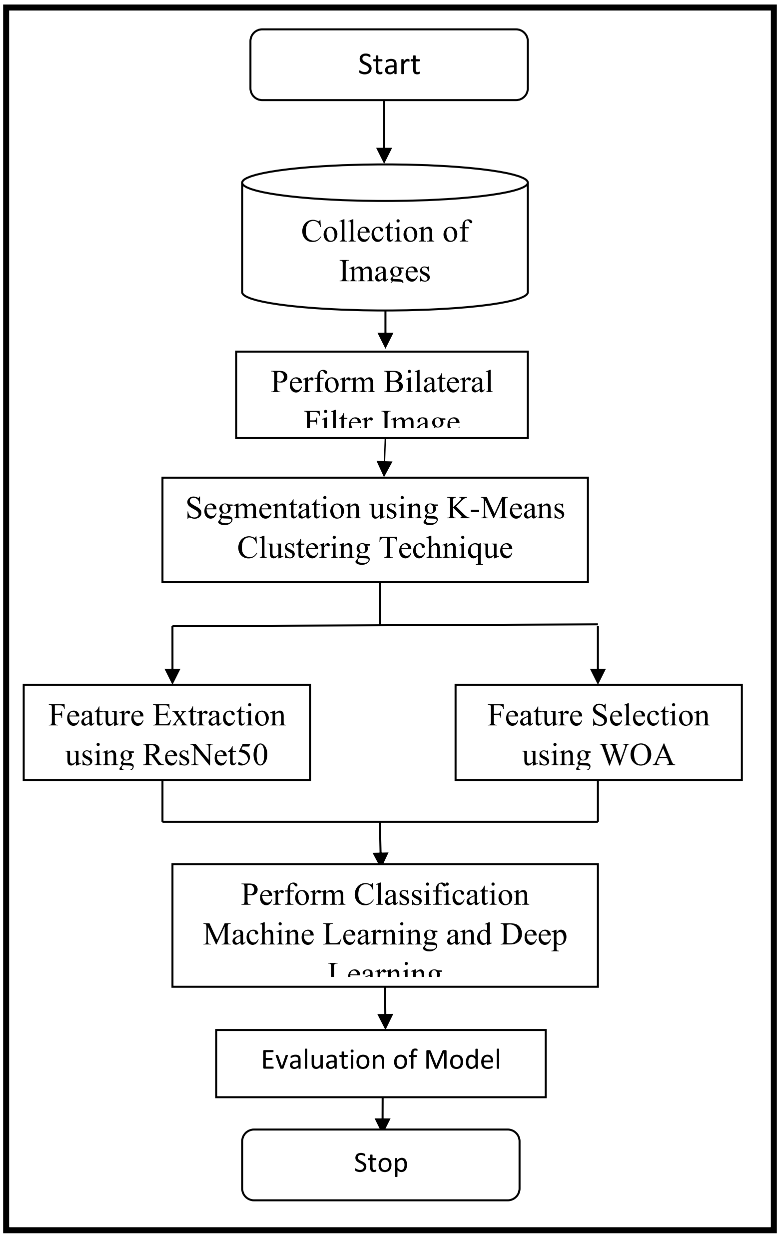

Figure 4: The Proposed Segmentation based Framework for Skin Lesion Detection

3.6. Working Mechanism

The operational process can be defined below:

Input: Get images for the processing

Output: Get output score and prediction for skin lesion cancer.

Step-1: Collects pictures and stores them in objects that include data.

Step-2: Convert data into descriptors to perform statistical computation.

Step-3: Use Bilateral Filter Image technique effectively reduces the presence of roughness, noise, and complicated details.

Journal of Information Systems Engineering and Management
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Research Article

Step-4: Begin the process of correlation to determine the pairwise score of descriptors. The BLOSUM approach does not calculate a score lower than the threshold value of 0.62 for a given size.

Step-5: Perform segmentation by identifying objective function is defined as the sum of the Euclidean distances among every instance of training and its corresponding cluster center, calculated across all k clusters using K-Means clustering algorithm.

Step-6: Perform feature extraction using ResNet50 model and feature selection using Whale Optimization Method (WOA) algorithm.

Step-7: By utilizing the chosen attributes construct the model utilizing a machine learning model and Deep learning approach.

Step-8: Perform classification and prediction.

4 RESULT AND DISCUSSION

The suggested approach consists of several sequential operations, including pre-processing, filtering, segmentation, feature extraction, and classification, as depicted in Figure 4. To evaluate the classification accuracy of the suggested model, a thorough investigation is carried out using two datasets, namely ISIC and HAM10000. This analysis utilizes five metrics and includes a comparison analysis to demonstrate the effectiveness of the method. The five-performance metrics that quantify the performance of a system are accuracy, sensitivity, specificity, precision, and F-1 score. These parameters also measure the AUROC (Area Under the Receiver Operating Characteristic) curve [29]. This indicates that the model will effectively assign a greater level of danger to a patient selected at random. An analysis comparing the proposed findings of lesion-based skin cancer simulations. The proposed method is supported by measures of specificity and sensitivity, which demonstrate its effectiveness. The proposed system is evaluated using the subsequent performance indicators. Table 1 presents the efficacy of the recommended datasets.

Table 1: Comparison between Different Classifier for (a) Support Vector Machine, (b) Convolutional Deep Neural Networks and (c) Deep Belief Network

Model	Parameter (%)	ISIC Dataset	HAM10000 Dataset
Support Vector Machine (SVM)	Accuracy	85.5	86.1
	Sensitivity	87.1	87.7
	Specificity	80.1	81.1
	Precision	88.7	89.3
	F1 – Score	88.2	88.3
	AUROC	90.1	90.6
Convolutional Deep Neural Networks (CDNN)	Accuracy	91.1	92.3
	Sensitivity	93.7	94.5
	Specificity	88.6	89.1
	Precision	95.1	95.7
	F1 – Score	94.5	95.1
	AUROC	96.1	97.3
	Accuracy	94.9	96.1

Deep Belief Network (DBN)	Sensitivity	95.7	96.1
	Specificity	89.9	90.5
	Precision	96.9	97.6
	F1 – Score	94.7	95.5
	AUROC	98.3	99.1

All three-machine learning Deep Learning methods are adequate for the model we have provided; but Deep Belief Network (DBN) outperforms the other two classifier's techniques. Figure 5 and figure 6 provide a graphical illustration.

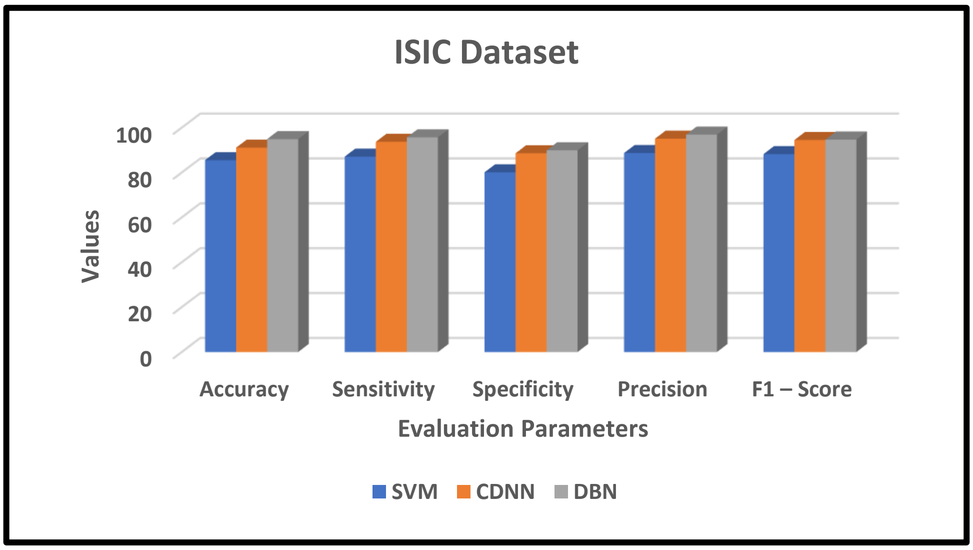

Figure 5: Analyse and compare the results of the suggested method using the ISIC Dataset.

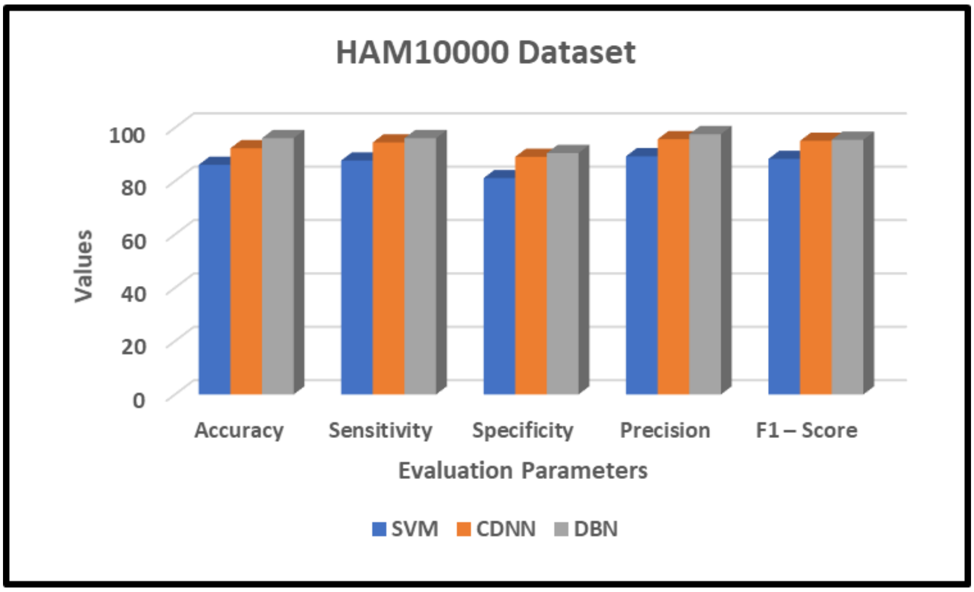

Figure 6: Analyse and compare the results of the suggested method using HAM10000 Dataset

Journal of Information Systems Engineering and Management
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Research Article

By examining the mean AUROC score, one may determine whether or not the classifier is performing at its ideal level. In figure 7, it is shown that the outcomes that are obtained by Deep Belief Network are superior to those that are accomplished by both of the two Machine Learning and deep learning techniques.

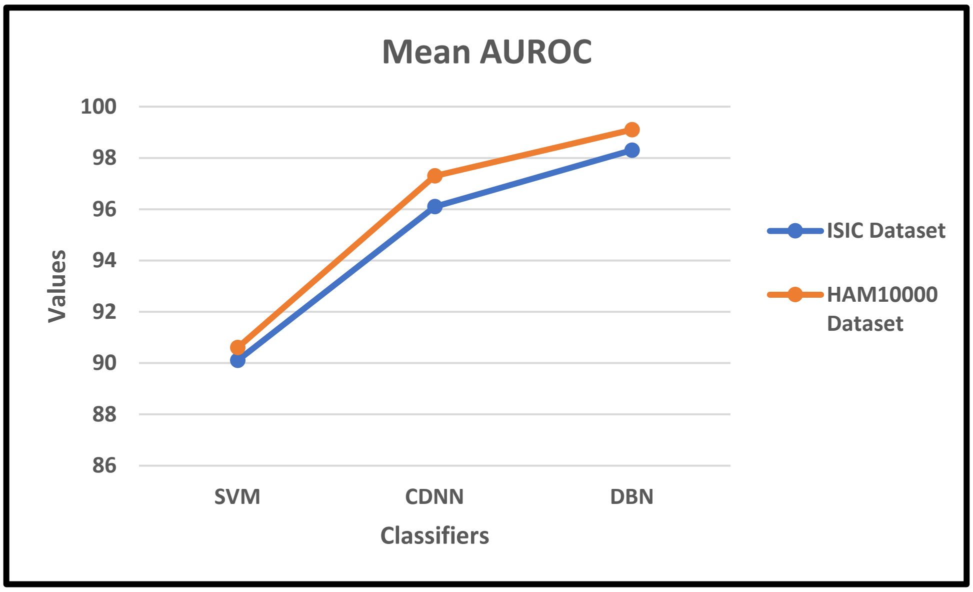

Figure 7: Analyse the effectiveness of employing both Machine Learning and Deep Learning algorithms.

5. CONCLUSION AND FUTURE SCOPE

This research presents a more effective and innovative approach that utilizes transfer learning approaches to enhance diagnostic accuracy. Due to the rapid increase in the incidence of skin cancer, there is an immediate need for a deep learning approach for the identification of skin lesions. Machine learning algorithms have been more valuable in the field of medical image interpretation and related areas. While there have been several advanced models mentioned in the literature, it is evident that strategies based on Deep Learning have shown superior performance when applied to dermoscopic skin lesion pictures. This project focuses on designing a collection of Deep Learning driven Computer Aided Diagonosis models for detecting and classifying dermoscopic skin lesions, taking into account the outstanding results of these models. This study has devised an innovative method that relies on models for segmenting and classifying skin lesions. The suggested technique comprises several steps, including pre-processing, segmentation, feature extraction, and lastly classification. The research activity has been structured into a three-part series of study goals. The first goal involves the acquisition and preparation of data. A second aim has been presented, which involves performing segmentation using RSNet50 and conducting feature extraction and selection for the identification of skin lesions from dermoscopic images. The third aim involves the development of a classification model for diagnosing skin lesions. Based on the analysis of the tables and figures provided, it is evident that the DBN model has achieved the highest level of classification performance. Specifically, it has shown a sensitivity of 94.1%, precision of 96.6%, and accuracy of 93.9%. The suggested models are evaluated for performance on the standard ISIC dataset and HAM10000 Dataset. The outcomes are analyzed from several perspectives. The testing results demonstrated the improved efficiency of the provided models compared to the current models stated in the survey part. Out of the three models that were suggested, the Deep Belief network (DBN) has been determined to be more successful than the other models. Thus, it may be used as a suitable instrument for real-time diagnosis of skin lesions.

The effectiveness of the proposed models may be enhanced by using advanced segmentation techniques based on deep learning techniques, which will be explored in future research. Moreover, in the future, adjusting hyper parameters of deep learning algorithms could be used to enhance classification accuracy to a greater extent.

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