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Analysis Of Support Vector Machine And Resnet-50-Based Skin Cancer Detection

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Abstract: *This paper focuses on the application of algorithms available in machine learning, particularly Support Vector Machines (SVM) as well as Resnet-50, in the classification of dangerous skin cancer from epiluminescence microscopy images. The study analyzes effectiveness of the two models on accuracy evaluation metrics that include confusion matrix, graphical plots, Receiver Operating Characteristics (ROC) and attempts to find which model more optimally detects skin cancer. Previous studies indicate that Resnet-50 outperforms SVM in detection accuracy capabilities. Thus, the purpose of this paper is to also showcase the ability to enhance perception accuracy for skin cancer by integrating both models. The results of this study are clinically relevant. With the implementation of computer-aided diagnosis (CAD) systems, clinicians are now able to make reliable diagnoses of skin cancer which lessens the degree of subjective variability between different clinicians and enhances clinical objectivity. The study emphasizes the diagnosis and treatment of skin cancer using machine learning models, which improves patient consequences. The abstract highlights significant insights on the performance of models present in machine learning for detecting skin cancers and becomes a useful resource for clinicians and researchers who consider adapting the use of machine learning in skin cancer detection.*

Keywords: *ABCD criteria, Melanoma, Skin cancer, SVM, RESNET-50*

1. INTRODUCTION

Globally, one of the most widespread and dangerous types of cancer is skin cancer. Its discernment in earlier stages is vital for effective medical treatment and enhancing the patient's condition of life. Integration of Artificial Intelligence (AI) into diagnostic workflows is becoming easier, especially with the accessibility of dermoscopic imaging through computer-aided diagnosis (CAD) systems. A dermatologist's clinical judgment has always been the backbone of skin cancer diagnosis, but his assessment is often influenced by personal bias and interobserver variability. ML and DL techniques are being implemented to bolster variability within cancer diagnostics using objective, consistent analytical support.

Support Vector Machines (SVM), an ML algorithm based on supervision, has successfully been applied to classification problems with structured and high-dimensional data. At the same time, deep learning models, particularly Convolutional Neural Networks (CNNs), have achieved remarkable accuracy with diagnostic tasks that rely on images. One of them is ResNet-50, a deep residual network of 50 layers which is well known for high accuracy image classification as it overcomes the vanishing gradient problem, allowing deeper networks to be trained.

This research intends primarily to assess and benchmark how Support Vector Machine (SVM) and ResNet-50 models perform in classifying dermoscopic images taken of the skin lesions. The objective is to understand the performance differences between traditional machine-learning approaches and deep-learning frameworks in skin cancer detection. Emphasis is placed on evaluating the advantages and shortcomings of each model using multiple benchmarking techniques such as accuracy, the confusion matrix, and Receiver Operating Characteristic (ROC) curves. Another important goal is to assess the possibilities for the implementation of SVM and ResNet-50 in a hybrid diagnostic approach. The synergy from this integration is expected to improve the classification accuracy and reliability align with the complementary strengths of both. Furthermore, the study aims to play a role towards the overarching goal of achieving intelligent, automated computer-aided diagnosis (CAD) systems. Such systems could enable dermatologists to rapidly and accurately diagnose skin cancers, which enhances the clinical decisions and the patient's health outcomes.

For this research, the author has taken up several important activities so that the study remains balanced and meaningful. The dermoscopic image dataset was obtained carefully and underwent initial processing so that it could be assessed with both machine learning (ML) as well as deep learning (DL) models. The author developed and executed distinct classification models based on SVM and ResNet-50, focusing on tuning the parameters and optimizing the models for evaluation. A thorough comparative evaluation was performed using various statistical measures and visual representation such as confusion matrices, ROC curves, and accuracy score to evaluate and graphically represent the models' effectiveness.

The author formulated and evaluated a new hybrid diagnostic method that merges the functionality of SVM and ResNet-50 in addition to assessing each model independently. This combination sought to harness the capabilities of each model toward enhancing and skin cancer detection. The author also extracted and explained the findings of the study concerning their applicability in a clinical setting. All in all, this study integrates traditional ML techniques with contemporary DL frameworks, illustrating the synergistic interplay of both approaches in classifying medical images. The results highlight the promising impact of AI on dermatology and support the continuous efforts to develop automated skin cancer diagnosis tools.

In order to derive a well-grounded and applicable strategy for skin cancer detection, it is important to review other research within the same discipline. A literature review sheds light on the techniques, datasets, and evaluation benchmarks employed in previous work, exposes model underutilized opportunities, and highlights the advantages and gaps present in machine learning and deep learning for medical image analysis. These excerpts need to be presented in these particular ways for asynchronous validation as well as proper contextualization of the essential work within additional pieces of the targeted research gap.

2. LITERATURE REVIEW

Cutaneous cancer is gaining more attention with the increased exposure to ultraviolet rays and early intervention is extremely important in decreasing rates of mortality. Deep learning techniques are nowadays implemented to skin cancer identification through analyzing lesions for symmetry, color, dimensions, and shape [10]. There has been some experimentation for the implementation of image capturing that is associated with deep learning models which employs Resnet 50 as well as SVM for the classification of dermoscopic images. The precision of this proposed research is validated with ABCD method and the Seven Point Checklist of dermoscopy routines. Such advancements in technology skin cancer detection increase accuracy while also reducing the cost and time of proper treatment [1]. Skin cancer is advanced cancer that develops from the epithelial tissue present in the skin and is mainly caused by continuous skin contact with ultraviolet (UV) radiation. It includes seven principal forms which are basal cell carcinoma, squamous cell carcinoma, melanoma, and the latter being the most dangerous. Risk factors for this include people with fair skin, a record of sunburns, languished immune system, application of tanning beds, and family history of skin cancer. Diagnosis is done by skin biopsy, with various treatment options including surgical removal, radiation therapy, chemotherapy, and immunotherapy. Defining discernment coupled with early treatment are essential in ensuring a favorable prognosis, while individuals can actively reduce the risk by not getting sun exposure as well as wearing protective clothing along with sunscreen. Skin cancer's primary cause centers around ultraviolet radiation exposure, whether directly from the sun or through tanning beds. This type of radiation may damage the skin’s DNA, leading to the noncontrolled growth of skin cells. Some of the other risk factors include heritable factors, exposure to arsenic-containing chemicals, and an organ weakening immune system. Skin cancer challenges can be tackled effectively by reducing exposure to ultra violet radiation, in addition to taking protective measures such as the use of sunscreens and protective clothing. Compromised immune systems and a familial past of skin cancer necessitate heightened caution. Diagnosis of skin cancer has been aided by machine learning as well as deep learning techniques like Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Random Forests with Transfer Learning methods. To identify skin cancer, models like SCC-CNN, SLAM, and other CNN architectures work alongside SVM derived models which classify skin lesions by textures and colors [2, 13, 15]. Ensembles of decision trees are utilized by random forests to classify skin lesions as benign or malignant using textures and colors as parameters, subsequently amalgamating the forecasts [3]. Transfer learning in neural networks is the practice of teaching new models to detect skin cancer employing previously acquired knowledge from other networks [4]. As these technologies mature, the reliability and efficiency of skin cancer detection will continue to improve. While promising, these ML and DL approaches also face challenges in the context of skin cancer detection [6]. CNNs tend to be the most sophisticated in detection, yet training a CNN requires an abundance of data and computational resources making them highly expensive. SVMs and random forest models may not perform to the same standards as CNNs on intricate datasets, but they do require significantly less computational power. 14]. Pre-trained models are the basis for transfer learning, which means the model used for one task might not be compatible with different tasks. Moreover, if the models are trained on homogeneous data, they may also suffer from bias. Hence, more work is needed to refine these methods in order to overcome the identified gaps and enhance worsening factors such as primary accuracy sensitive to detecting skin cancer. Focus of the study is to portray the skin cancer which is one of the most critical issues in public health sense and causes more than five million newly diagnosed cases every year in the United States and worldwide. Skin cancer itself has two major forms of classification - melanoma, the more dangerous type, and non-melanoma skin cancer. Globally in 2015, there were approximately 350,000 reported cases of melanoma, which accounted for 60,000 deaths. Non-melanoma skin cancers, consisting largely of squamous cell carcinoma and basal cell carcinoma, are the most prevalent with over 1 million cases reported worldwide in 2018. Forecasts estimate that in 2022, almost 1.9 million new cases of non-melanoma skin cancer are expected to be diagnosed [5].

Table 1: Summary of Key Information on Skin Cancer and Its Detection Using ML/DL Techniques

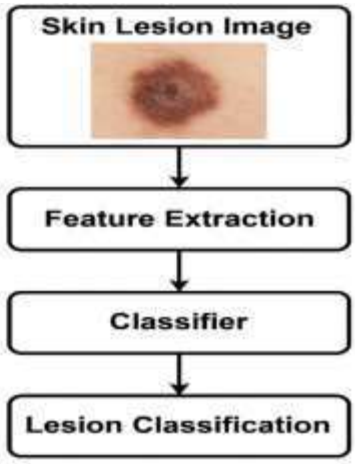
Category	Summary Details
Prevalence of Skin Cancer	Increasing due to UV radiation; over 5 million new cases annually in the U.S. alone.
Major Types	Melanoma (most severe), Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and other rare forms.
Risk Factors	UV radiation, fair skin, sunburns, tanning beds, weakened immune system, genetic predisposition, arsenic exposure.
Symptoms and Diagnosis	Lesion analysis (asymmetry, border, color, diameter), biopsy confirmation.
Treatment Options	Surgical removal, chemotherapy, radiation, immunotherapy.
Preventive Measures	Use of sunscreen, avoiding peak sun, wearing protective clothing.
Techniques for Detection	CNNs, SVM, Random Forests, Transfer Learning, SLAM, SCC-CNN models.
Hybrid Approach Used	ResNet-50 + SVM proposed for enhanced accuracy in dermoscopic image classification.
Evaluation Techniques	ABCD Rule, Seven-Point Checklist, ROC curve, Confusion Matrix, Accuracy scores.
Advantages of ML/DL Models	Faster, non-invasive, consistent, potentially high accuracy in diagnosis.
Limitations of Techniques	CNNs need large datasets and computing power;

	SVMs/Random Forests handle less complexity; transfer learning may not generalize.
Global Statistics	~350,000 melanoma cases (60,000 deaths) in 2015; ~1.9 million non-melanoma cases expected in 2022.
Research Goal	To improve early detection accuracy, reduce diagnosis time and cost using AI models.

Skin cancer is now a prominent health concern worldwide due to the increased risk associated with exposure to UV radiation. A patient's likelihood of survival and associated healthcare expenses is directly connected to their risk of melanoma, the most life-threatening melanoma which is generally more aggressive than non-melanoma skin cancers basal cell carcinoma and squamous cell carcinoma. Millions of new cases emerging each year entails a globally accepted method of precise and timely diagnosis. Techniques within deep learning and machine learning—like as CNNs, SVMs, Random Forests as well as Transfer Learning—have proved to be effective "dermoscope image" analyzers for skin cancer detection. Every technique, however, suffers from some deficiency—be it high computational cost, data dependence, model bias, or one-sided accuracy. A hybrid model of ResNet-50 and SVM is constructed with hopes of maximizing accuracy, balancing the opposing tendencies of each individual model. Standards such as the ABCD rule for melanoma and Seven Point Checklist allow higher reliability in diagnosing skin cancer. Advances in AI related diagnostic systems hold promise for quicker, cheaper, and reliable operational aids supporting decisions to detect clinically significant skin cancer faster and enhance patient care and outcomes [1].

3. CONVECTIONAL APPROACH

The standard method for addressing the problem of detecting skin cancer from dermoscopic photographs works in a sequence which guarantees the precision and dependability of the classification results. The first step involves acquiring quality images of the skin lesions. As the primary input for the pipeline, these images are obtained from medical databases and tend to have heterogeneous shapes, sizes, colors, and types of lesions. The objective at this step is to collect samples that are representative of both benign and malignant conditions and encompass a variety of skin conditions.



Next, we perform feature extraction, which is perhaps the most important step. With the older approaches to machine learning, this meant such processes as identification of color, texture, border irregularity, and other features such as contouring. These features extracted from the almost intricate data set while retaining the important information needed for classification. In deep learning models such as ResNet-50, automated feature extraction is performed by several stacked convolutional layers, which form hierarchically structured models of the input images. This is one reason deep learning models are preferred over traditional models for analysis of images; they acquire low-level and high-level features effortlessly.

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Following feature extraction, those features are sent to a classifier for recognition and decision-making. For this research, the classifiers are both a Support Vector Machine (SVM) and a ResNet-50 model. The SVM performs well with the extracted features in lower-dimensional spaces, creating optimal hyperplanes to separate different classes of lesions. Deep convolutional neural network ResNet-50, on the other hand, does not only feature extract but also classifies, performing both tasks in one framework. Thus, it is more efficient.

The concluding step is lesion classification, where the model decides the label of the skin lesion, which is most often benign or malignant. This is a second opinion automated diagnosis which is valuable to skin cancer specialists while streamlining their workflows enhances the diagnostic process. This systematic and traditional approach captures the essence of automating skin cancer detection and serves as a baseline for more complex and fusion strategies.

4. PROPOSED METHODOLOGY

4.1 Artificial Intelligence

AI aims to build smart machines that learn from data, adapt to new challenges, and devise plans of action. Algorithms as well as statistical models can accomplish this, along with machine learning methodologies, including deep learning through neural networks. AI is used in different areas like self-driving cars, analyzing images, and in the healthcare sector for tailoring treatments along with analyzing medical images [11]. On the other hand, AI poses ethical and social problems. job loss is a concern in automated production lines and transport systems AI might also be misused for hacking or spying, which is a concern AI development lack oversight; social transparency could be detrimental. There should be AI regulations dealing with safety and social implications. AI principles for the design of AI systems should be based on ethics focusing on social availability and equal access of AI services and welfare. Education, health and transportation are among sectors where AI introduction could be revolutionary. Timely actions could make sure that risks remain limited while benefits can be maximized, demanding prudent innovations, aimed AI development.” [7, 8]

4.2 Machine Learning

In essence, applying algorithms to detect as well as identify patterns and predicting or decision-making based on them is the core of machine learning, a category of AI. It relies on statistical algorithms and models to make computers to autonomously improve their performance on a given task through learning and available data. Supervised learning plus unsupervised learning, and reinforcement learning are the three primary subdivisions of machine learning [12].

4.3. Support Vector Machine

This technique involves using a trained algorithm that has access to a labeled dataset, where every instance contains a predefined input along with output. Reducing the differences between what the algorithm predicts and what the dataset contains, the algorithm learns during training to associate input data with the corresponding related output data. This methodology is applicable for numerous tasks, such as image classification, audio recognition, and natural language processing [17].

4.3 ResNet-50

ResNet-50 or Residual Network-50 is a type of convolutional neural network (CNN) architecture which consists of 50 layers. This architecture was designed by Microsoft Research and has several applications in computer vision such as object detection and image classification [16,18]. The” Residual” part of ResNet indicates that it incorporates the design with residual blocks. The presence of these blocks allows the network to learn residual functions because of the presence of skip connections. These links allow for the skipping of certain layers so that information is passed directly from earlier to later layers. This technique aids in the training of extremely deep neural networks and mitigates the vanishing gradient problem [19].

Variations of a number of layers can be found in the 50 layers of ResNet-50, including convolutional layers, pooling layers, fully connected layers, and shortcut connections. It is highly regarded to have great accuracy with image recognition tasks. ResNet-50 is also known to have great feature extraction capabilities. It is pre-trained on a large number of images, like ImageNet, so it recognizes distinct features and can be modified for specific visual recognition tasks later. [20]

4.4 Seven-Point Checklist Approach

Seven Point Checklist is a scoring system for evaluation of skin lesions based on seven criteria. This checklist originated in Glasgow in the 1980s intending to assist dermatology trainees and help non-specialists facilitate an approach towards camouflaged cases in a more systematic and precise way for diagnosis [24]. The 7 PCL checklist containing 7 points have certain criteria that suggest possible existence of malignancy cancerous lesions and warrant immediate specialist's attention [21]. The primary three indicators considered for skin cancer are a) increase in size; b) shape change; and c) color change. There are secondary indicators too: a) inflammation, b) crusting or bleeding, c) alteration in sensation, and d) 7mm or greater diameter.

4.5 ABCDE Rule

The ABCDE model is one of the most used techniques for the early detection of skin cancers. All letters have a certain characteristic analyzed for a skin lesion.

A: Asymmetry - Unevenness in shape and color may serve as an indication of concern for a lesion, hypothetically, if it does not match a symmetric counterpart.

B: Border irregularity - the borders of a lesion may be jagged or poorly defined, suggesting advanced stages of skin mutations. [25]

C: Color variation - Different colors shows that there are broken parts of skin cancer, including the parts of brown, black, red, white, and blue.

D: Diameter - More than 6 millimeters of lesion breakage could be a warning sign to be observed.

E: Evolution- Any changes over time in size, shape, color, or elevation should be analyzed in-depth by professionals since they might be indicative of skin cancer.

These attributes allow one to monitor carefully for any changes in the skin for possible indicators of skin cancer and get medical assistance immediately if anything unusual is found [22].

4.6 HAM10000 Dataset

HAM10000, or Human against Machine with 10000 training images, is a dataset of dermatology images that is publicly available and intended for developing and benchmarking machine learning algorithms related to skin lesions classification. The dataset have 10,015 dermatoscopic images of skin lesions which were collected from utf-derm and are divided into seven different diagnostic categories. It was published in 2018 by the department of dermatology, medical university of Vienna.

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1. Working Model

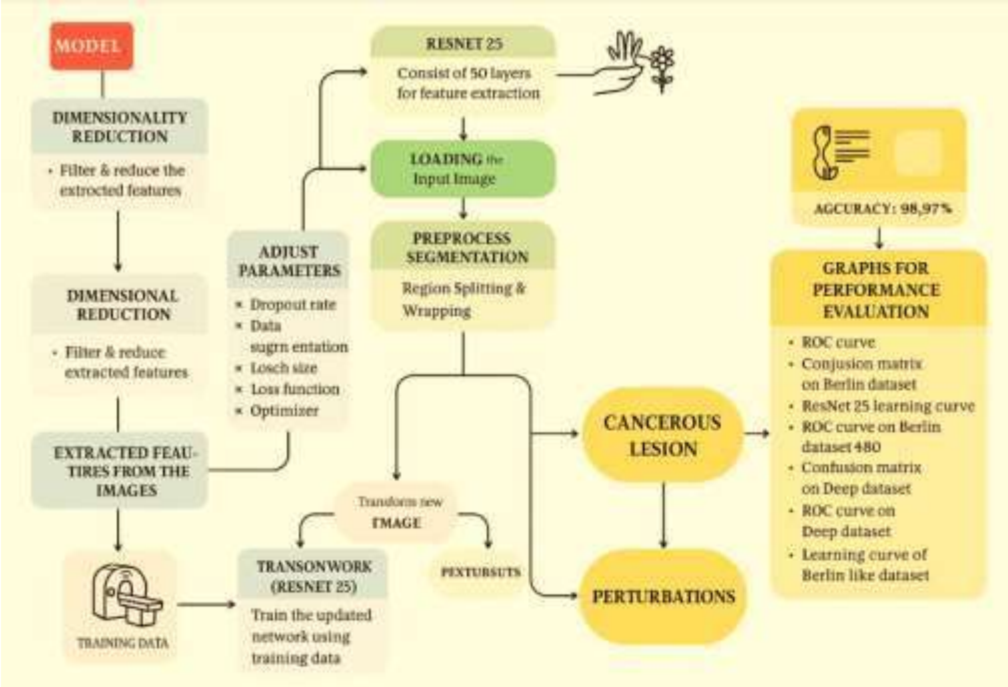

Fig. 1 Block diagram of proposal methodology

Functional model considered of our project is demonstrated in the accompanying diagram. In the world, skin cancer is a commonly known and diagnosed type of cancer, and their timely treatment is crucial. For any form of skin cancer, most practitioners utilize the ABCD technique as well as the seven point checklist technique for initial detection of skin cancer. Under the ABCD approach, moles are graded on the basis of Asymmetry, Border irregularity, Colour variation, and Diameter stem. The seven point checklist approach, on the other hand, rely in more additional features such as age, gender, and skin cancer history as part of the evaluation. The development of effective machine learning algorithms in recent years made it possible to develop reliable computer systems for skin cancer detection in the early stages. Two models are Support Vector Machines (SVMs) and ResNet-50, a convolutional neural network.

While using the ABCD and the seven-point checklist methods, these models demonstrated accuracy rates as high as 98.77 percent when trained on skin cancer images. This indicates that the models can aid in the skin cancer detection process, assisting dermatologists in diagnosing skin cancer at an incipient stage. It can be concluded that machine learning models, particularly SVM and ResNet-50, have the potential to enhance the early detection of skin cancers remarkably. Achieving high accuracy with the models means that dermatologists would be able to detect cancerous moles much sooner, improving patient care.

6. EXAMINATION AND ANALYSIS OF RESULTS

As part of testing skin cancer detection with SVM and ResNet-50, the HAM10000 dataset will first undergo preprocessing, which entails resizing dermatoscopic images per skimming, normalization and augmenting. In this case, augmentation will include generalization-enhancing rotations, flips, and zooming. The dataset is split into distinct sets for training, validation, and testing, which is done in an 80-10-10 percentage ratio. To perform feature extraction, a deep convolutional neural network interred with residual connections will be used to register greatly intricate features of the images into the patterns. The skin lesion dataset can be leveraged to retrain the ResNet-50 model by attaching a Support Vector Machine (SVM) classifier on its output layer to perform skin cancer classification at a finer granularity. The SVM is further tuned with various kernel functions and hyper parameters to

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attain the optimal decision boundary. To report the results, the model's performance is assessed on a test set and the performance metrics calculated include accuracy, precision, recall, F1-score, thereby evaluating the effectiveness of the hybrid model on the multi-class skin cancer lesion detection tasks.

The accuracy results of applying the SVM classifier and the ResNet-50 skin cancer models with the ABCD and seven-point checklist techniques yielded accuracy levels of 98.77%. This model could ascertain with certainty the cancerous nature of moles based solely on their visualization and medical history data. Such accuracy was confirmed through a test set of images not presented to the model during its training phase. Moreover, graphical metrics were one of the means the evaluation of the model’s performance was conducted. In conclusion, the findings demonstrate the usefulness of these machine-learning models to support dermatologists in diagnosing skin cancer at an earlier stage.

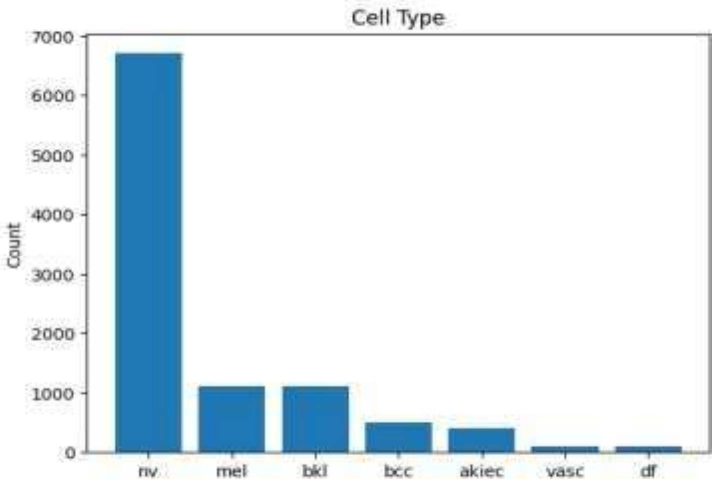

Fig.2 Plot of Count vs Cell Type

The chart demonstrates the count-based distribution of various cell types. Cancer cases of the skin that are correctly grouped include actinic keratoses and intraepithelial carcinoma/Bowen’s disease (AKIEC), basal cell carcinoma (BCC), benign keratosis-like lesions (BKL), dermatofibroma (DF), melanoma (MEL), melanocytic nevi (NV), and vascular lesions (VAS). Out of the listed types, melanocytic nevi (NV) is most prevalent while vascular lesions (VAS) and dermatofibroma (DF) are the least prevalent.

Count vs Sex Plot

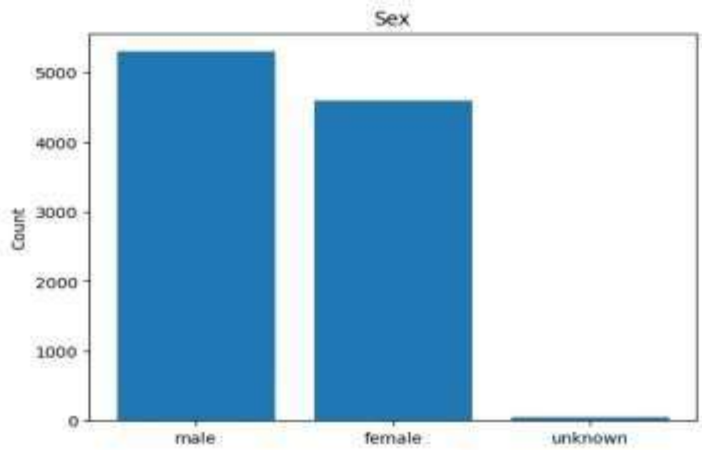

Fig.3 Plot of Sex vs Count

The lplot captures the number of cases that pertain to male patients as well as female patients. Many more cases are there where the gender is not specified. From the plot, it can be noted that skin cancer cases in male patients are higher relative to female patients.

Count vs. Localization Plot:

The graph illustrates Localization vs Count. The gastric region is delineated into the following back, lower back, trunk, upper limb, abdomen, face, chest, leg, neck, scalp, hand, ear, genital, acral and other non-specific regions. The maximum numbers are seen recorded on the back while least on the acral area.

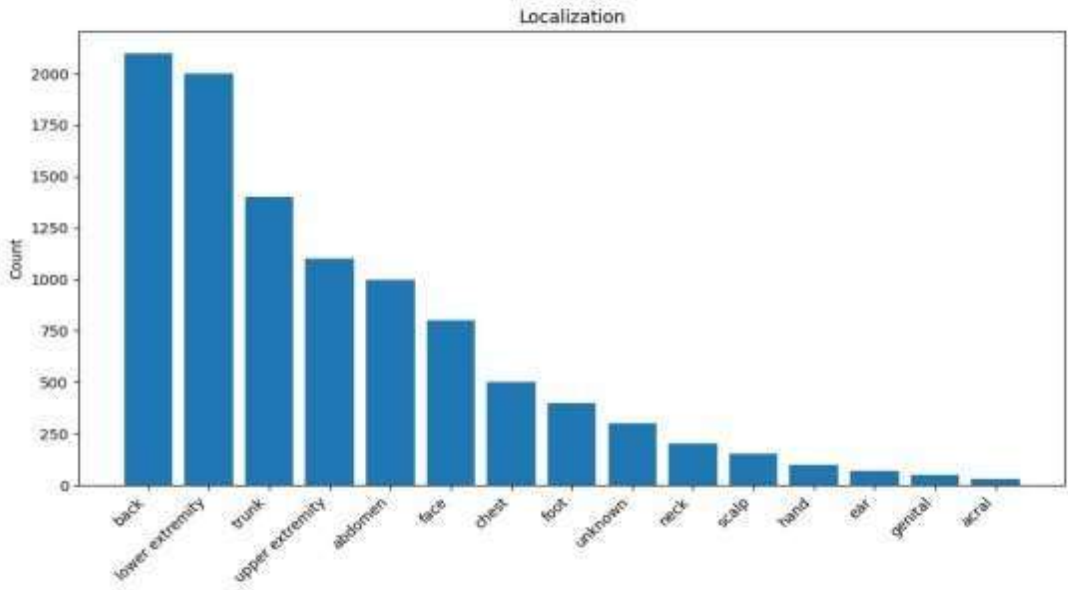

Fig.4 Plot of Localization vs Count

Age vs Density Plot:

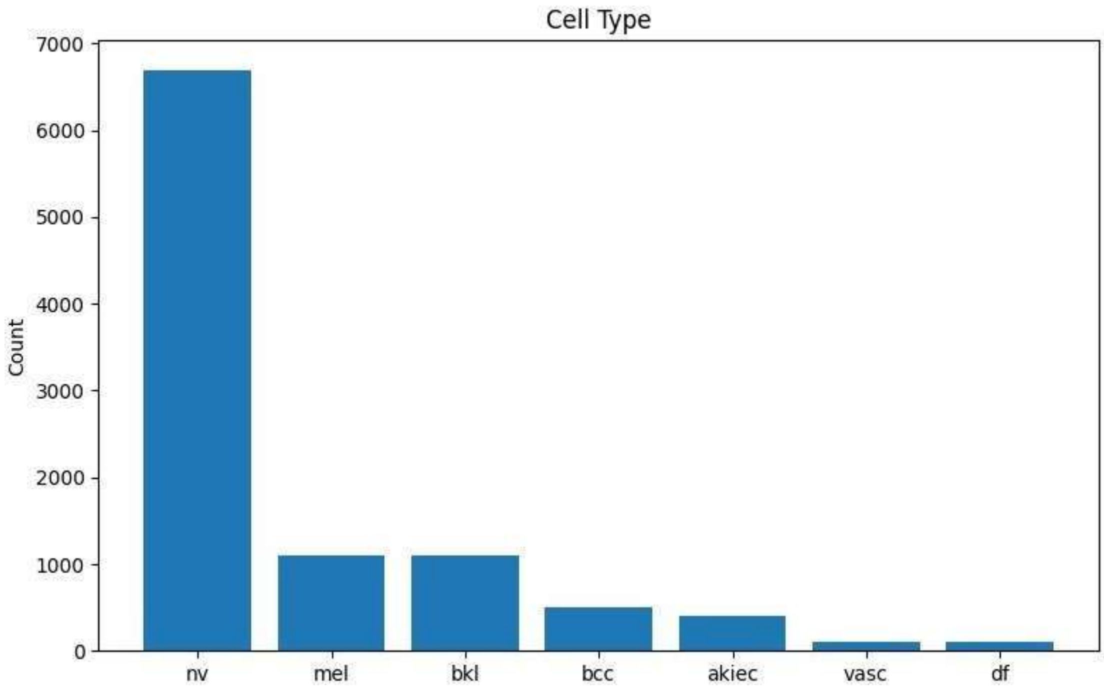

Fig.5 Age Vs Density Plot

This particular plot depicts the several ages of patients and the frequency of patients diagnosed with skin cancer at a specific age. In the plot, it can be noticed that the maximum skin cancer cases fall within the skin cancer patients aged between 40 to 60 years old. Infants and young people aged from 0 to 20 years of age have the least skin cancer cases.

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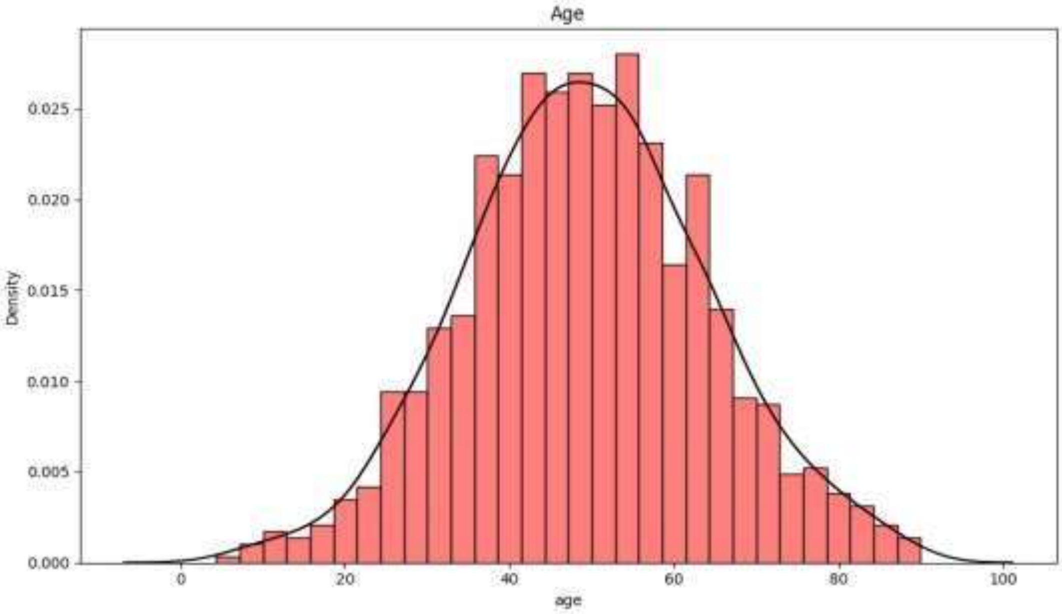

Fig. 6 Classified images of the dataset by the proposed Model

We implement our model with the HAM10000 Dataset that represents a collection of 10,000 photos taken of skin cancers. The purpose of this model is to classify these images into specific seven distinct kinds of skin cancer which are basal cell carcinoma (bcc), actinic keratoses and intraepithelial carcinoma/Bowen's disease (akiec), benign keratosis-like lesions (bkl), melanoma (mel), melanocytic nevi (nv), and vascular lesions (angiomas or angiokeratoma). Results are given by the model as shown in the related figure 6.

Accuracy and Further Results

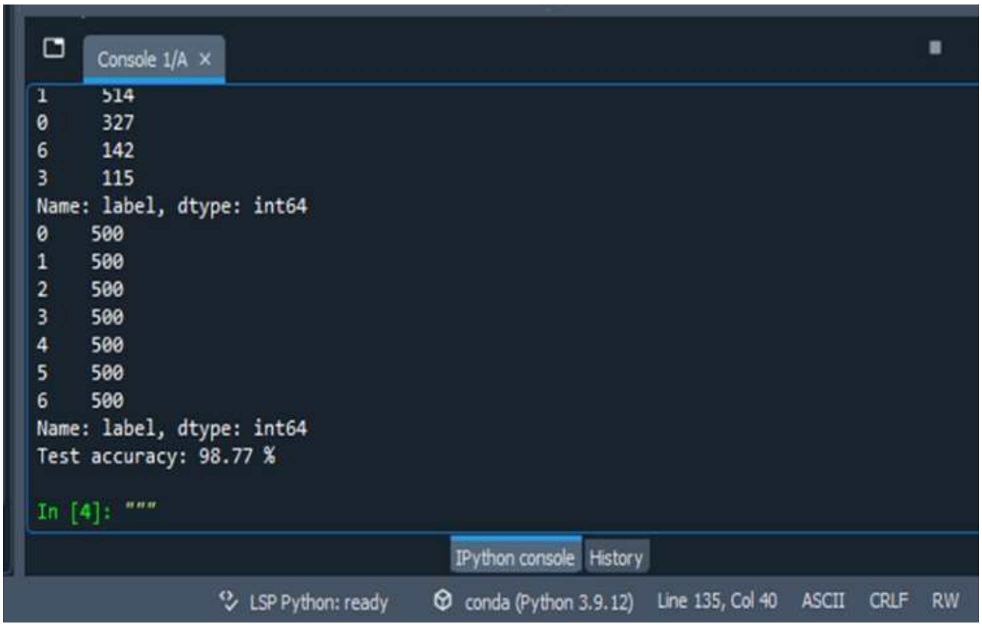

Fig. 7 Accuracy of the working model

The accuracy of developed model is reported to be 98.77%. The reason why this model is attaining such a high accuracy rate is because of the appropriate features-based cancer mole image recognition from the image-processing techniques utilizing Resnet-50 together with ABCD and Seven-point Checklist method.

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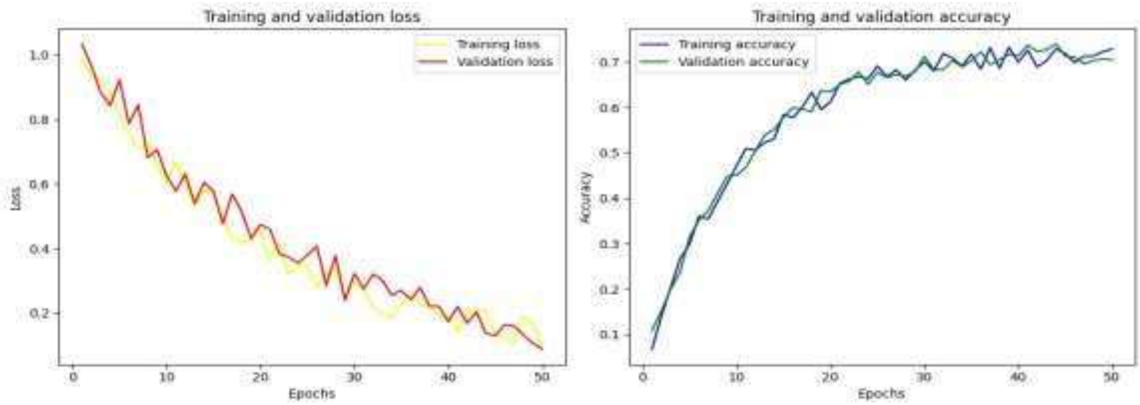
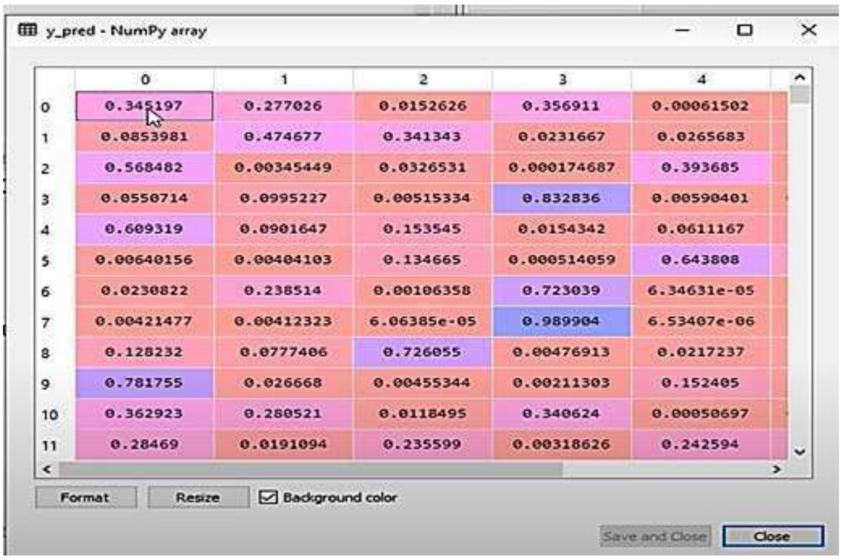


Fig. 8 Training and Validation Curves

In the relatable training a neural network, epochs represent the number of complete iterations made by a machine learning algorithm on a given dataset. An epoch consists of one cycle where the model attempts to work with every sample in the training set once. The aims of training a neural network is to maximize its forecasts through a process known as loss minimization. The number of epochs allocated for training a neural network is a crucial hyperparameter as it greatly influences model performance. Insufficient epochs result in underfitting, where a model's design is too simplistic to capture the details of the data. In later part of study, too many epochs may lead to overfitting, where the model becomes too well versed to the training set and struggles to generalize to new, unseen data. For our case, we are performing 50 Epochs each of batch size 16 with a dataset containing 2625 images for model training. In the graph above, the loss versus epochs curve is presented and this curve do not depicts tendency towards overfitting or underfitting. The training as well as validation curves almost overlap and as the epochs increase, the curve continues to decline.

Moreover, in the curve displayed next, the x-axis is labeled with epochs which is the increase in number contrary to the previously stated accuracy and y-axis represents the accuracy slope. The accuracy curve demonstrating increasing tendency for a number of epochs is quite noteworthy. Both curves provide evidence of successful implementation of the code.


y_pred - NumPy array

	0	1	2	3	4
0	0.345197	0.277026	0.0152626	0.356911	0.00061502
1	0.0853981	0.474677	0.341343	0.0231667	0.0265683
2	0.568482	0.00345449	0.0326531	0.000174687	0.393685
3	0.0550714	0.0995227	0.00515334	0.832836	0.00590401
4	0.609319	0.0901647	0.153545	0.0154342	0.0611167
5	0.00640156	0.00404103	0.134665	0.000514059	0.643808
6	0.0230822	0.238514	0.00106358	0.723039	6.34631e-05
7	0.00421477	0.00412323	6.06385e-05	0.989904	6.53407e-06
8	0.128232	0.0777406	0.726055	0.00476913	0.0217237
9	0.781755	0.026668	0.00455344	0.00211303	0.152405
10	0.362923	0.280521	0.0118495	0.340624	0.00050697
11	0.28469	0.0191094	0.235599	0.00318626	0.242594

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Fig.9 Probability Prediction Table

We employ the SoftMax function that outputs all predictions in probabilities. It is applicable for multiclass classification problems, where the objective is to assign an input for instance to one of the

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various possible classes. In the subsequent table, each element of the output vector indicates the particular class probability. The class which has the highest liability for an element is deemed to come under that class. It indicates the likelihood that an image falls under a particular category or class. We then apply the argmax function to transform these probabilities into binary form (0s and 1s) and predict the class for each element. This probability matrix provides, in simple terms, the estimation of membership of a specific element to a defined class.

Fig . 10 Confusion Matrix

The designed system's accuracy on how well the photos is categorized corresponds to the confusion matrix. The predicted labels of class are represented by the number of columns present in matrix while the actual class labels are considered in the form of rows. The entries of the confusion matrix can be described in the following way:

TP: True Positives - This refers to the number of photos present in the model accurately detected as a particular class. For example, the bottom right cell of the confusion matrix shows the true positive value where melanoma pictures were correctly identified as melanoma pictures.

True Negatives (TN): This reflects the number of photos where the model correctly identifies a class but it is a different class altogether. For example, it shows the correct classification of non-melanoma images in the confusion matrix's upper left corner.

False Positives (FP): This is the number of images that were incorrectly labeled by the developed model that belong to a specific class. The upper right cell visible in the confusion matrix shows the false positive value of non-melanoma images being incorrectly labeled as melanoma.

False Negatives (FN): This describes the case of images belonging to a certain class which is incorrectly foretelled by the model as not being that class. For example, the entry seen in the bottom left corner visible in the confusion matrix is the false positive value for the melanoma images which are incorrectly classified as non-melanoma.

As a conclusion, the confusion matrix gives an understanding of how accurately the model is predicting given classes with respect to correct and incorrect predictions made by the model.

5. CONCLUSION

Skin cancer is a pervasive category of cancer that influences a large number of people worldwide, the uncontrolled growth of abnormal skin cells is usually triggered by factors such as ultraviolet radiation, genetic makeup, environmental exposure, and much more. Skin cancers may include melanoma, basal cell carcinoma, and squamous cell carcinoma among others. Skin cancer along with its associated complications can greatly affect the well-being of any individual which is the reason why therapy and early detection is so crucial. There has been a rising trend aimed at utilizing machine learning as well as deep learning algorithms to examine skin cancer. Such techniques are likely to improve the accuracy of skin cancer discovery while reducing the requirement of unwanted biopsies. In particular, Support Vector Machines (SVM) as well as deep learning models like ResNet-50 had shown remarkable success with skin cancer detection. Support Vector Machines SVM is one of the most popular and widely adopted machine learning classification algorithms. It identifies the optimal separation boundary in the midst of two groups of data, for example, benign as well as malignant skin lesions. Several researches implemented SVM for skin cancer detection where it was reported to yield high accuracy.

Unlike others, ResNet-50 performs exceptionally well when classifying images, earning it a gracious reputation as a deep convolutional neural network. Its ability to identify intricate patterns and features means it can be used for skin cancer detection. ResNet-50 outperformed all models in its accuracy with deep-learning skin cancer detection. SVM combined with ResNet-50 has positively detected improvement in the accuracy of skin cancer. We analyzed skin cancer lesions and demonstrated the accuracy achieved by the SVM classifier paired with ResNet-50. We also employed HAM10000 dataset images applying the ABCDE Method as well as 7-Point Checklist techniques for advanced feature extraction after image preprocessing. Medical doctors use the 7-Point Checklist method alongside the ABCDE Technique to validate the presence of cancerous skin lesions—deeming them as either malignant or benign. Our project was based on the analysis of all methods aforementioned. Automatically classifying images of lesions in the HAM10000 dataset comprises of seven kinds of skin cancer: Basal cell carcinoma (BCC), Dermatofibroma (df), Vascular lesions (vasc), Melanocytic nevi (nv), Melanoma (mel), Actinic keratoses & intraepithelial carcinoma (akiec), and Benign keratosis-like lesions (bkl). The accuracy measured by the developed system was 98.77 percent. This figure surpasses the achievements of SVM and ResNet-50 used independently, as well as the accuracy considered by dermatologists in any kind of study. All in all, employing SVM as well as ResNet-50 for skin cancer finding is a good idea and can be used for the initial diagnosis as well as treatment of life-threatening disease. Possible advantages of this algorithm are decreasing the rate of the requirement of unwanted biopsies and improving overall patient care. Although, to demonstrate the model's efficacy for use in clinical environments, advanced work is necessary to optimize the algorithms.

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