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ARTIFICIAL INTELLIGENCE BASED DERMAL CANCER DTETECTION USING COMPUTER VISION

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Abstract

Background*: Cancer is a leading global health concern, with early and precise detection playing a critical role in improving patient survival rates. Traditional diagnostic methods, while effective, often involve delays and human limitations. Recent advancements in artificial intelligence (AI) and machine learning have introduced new possibilities for enhancing diagnostic accuracy and efficiency, particularly through automated image analysis.* ***Objective****: This study aims to explore AI-driven techniques for cancer detection, focusing on deep learning models that analyze medical images to differentiate between malignant and benign tumors. The research evaluates various machine learning algorithms, assessing their accuracy, reliability, and potential for clinical application.* ***Results****: The findings demonstrate that AI-based diagnostic models can significantly improve the precision of cancer detection. Comparative analysis of multiple algorithms reveals that deep learning approaches, particularly convolutional neural networks (CNNs), achieve high accuracy in identifying cancerous lesions. The results suggest that AI integration in diagnostic processes can enhance early detection, reduce human error, and support medical professionals in making more informed decisions. This study reinforces the potential of AI-driven solutions in revolutionizing cancer diagnosis, paving the way for faster and more accurate detection, ultimately improving patient outcomes.*

Keywords*: Computer Vision, Melanoma, Classification, Segmentation, Skin Cancer, Detection, Dermoscopy.*

INTRODUCTION

Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) have demonstrated success in the early detection of skin cancer by utilizing various datasets and hybrid models, highlighting their potential in enhancing diagnostic accuracy (Shah et al., 2023). The primary cause of skin cancer is exposure to ultraviolet (UV) radiation, which damages DNA in skin cells when unprotected, leading to abnormal cell growth and potentially resulting in cancer. Among skin cancers, malignant melanoma is the most lethal, claiming nearly 11,000 lives annually in the United States (Suja et al., 2023). This aggressive cancer originates in the outermost layer of the skin and progressively invades deeper layers. If left undiagnosed, it can reach blood and lymphatic vessels, increasing the risk of metastasis. However, when detected at an early stage, melanoma can be surgically removed before it spreads to other tissues and organs, significantly improving patient outcomes (Shah et al., 2023; Suja et al., 2023). However, advanced malignant Melanoma that has spread to other organs is difficult to treat. That's why that stage of melanoma is deadly (Al-Amin et al., 2015). If we can distinguish malignant from benign Melanoma quickly, survival rates will improve. Two categories of skin cancer lesions exist. Two categories of lesions exist: malignant and benign. Melanin deposits are found in the

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epidermis of benign lesions, often known as common nevi. Malignant lesions produce melanoma at an abnormal rate. Malignant skin lesions generally pose no significant risk as long as melanocytes and melanin remain confined to the epidermis. However, when these cells invade the dermis and form deposits, noticeable changes in skin pigmentation occur. The Skin Foundation of Britain estimates that approximately 100,000 new cases of skin cancer are diagnosed each year, with around 2,500 fatalities attributed to the disease (Al-Amin et al., 2015). According to UK Cancer Research, 14,509 melanoma cases were recorded in 2013, and projections suggest that the number of affected individuals will continue to rise in the coming years. In the United States, research estimated that 83,510 new cases of malignant skin cancer would be diagnosed in 2016.In 2021, 13,500 deaths were reported (Chaturvedi et al.2021). Late-stage malignant melanoma is untreatable nowadays. Thus, early diagnosis is necessary to reduce mortality, health risks, and treatment costs. Expert dermatologists struggle to recognize early Melanoma from other pigmented skin lesions. In early stages, basic healthcare workers may misinterpret Melanoma. Thus, it intrigues researchers. Future scholars should have access to a current literature review. Thus, the author discusses the latest computer-based skin treatment system methods. State-of-the-art efficiency analysis is also done utilizing several efficiency measures. Almost all computer-aided skin infection diagnosis methods follow a similar pattern.

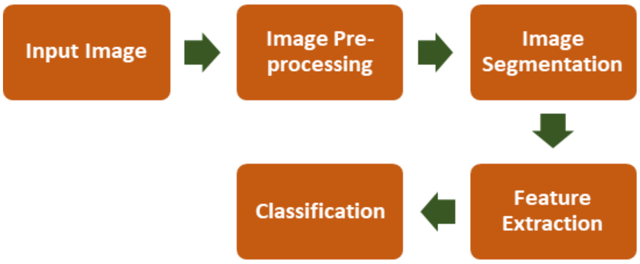

Figure 1: Steps Involved in Skin Cancer Detection

This review explores classification techniques, feature extraction, and segmentation, providing an in-depth analysis of different preprocessing, segmentation, and categorization methods. Additionally, mobile-based approaches for detecting skin diseases were examined. The assessment of existing research considered factors such as dataset usage, computational time, and overall efficiency. Computer vision techniques play a crucial role in distinguishing between malignant and benign cells. The implementation of computer vision in industrial sectors has significantly increased over the past few decades across various industries, including security, retail, healthcare, agriculture, and transportation. This growth is attributed to the accessibility of advanced visual systems and visual sensors. Computer vision has garnered significant attention from the construction sector due to its potential to automate essential operations, such as item detection, identification, surveillance, as well as motion, performance, and position estimation. Advancements in technologies and their growing application in construction projects over recent decades have led to a diversification in the development of computer vision. A literature survey is considered an efficient method for gaining a comprehensive understanding of a research topic. Recent review articles examine fundamental computer vision techniques employed in the detection of skin cancer. Computer vision techniques have been employed to identify hazardous conditions and behaviors, aiming to promptly mitigate potential risks in construction projects. Nonetheless, its implementation remains in the initial phases. This highlights the significance of notable scientific advancements and challenges in the realm of technical and practical autonomous vision-based wellness and security surveillance (Suja et al., 2023). This study examines the existing literature on skin cancer detection in web applications and compares AI tools based on computer vision for the early detection of skin cancer using dermoscopic images.

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LITRATURE REVIEW

Melanoma is the deadliest non-melanoma skin cancer. Melanoma, a cancer caused by abnormal melanocyte proliferation caused by excessive sun exposure, is on the rise (more than one million occurrences each year). Every type of cancer must be detected early to improve survival. For skin cancer detection, AI-based algorithms were built and an excellent tool for neoplasm recognition was found. Global Part Convolutional Neural Network (G-P CNN) AI-based categorization was applied for skin lesion and full body image analysis, from minor moles to old pathologic incisions or infections (Strzelecki et al., 2024). Local Binary Pattern (LBP) and Contourlet Transform (CT) techniques detected dermatoscopic cancer images' shapes, contrast, and borders, but Particle Swarm Optimization (PSO) classification was used due to potential and computational cost issues, which selected discrimination and reduced feature dimensionality. After applying features to Support Vector Machine (SVM), Neural Networks (NN), and Random Forest (RF), SVM and NN were faster and less complex than RF, and this proposed model PSO had 86% accuracy (Natha & Rajeswari, 2024). ResNet50 model, using SVM, k-NN, NB, and RF ensembles, outperforms Art-classifiers in detecting dermatoscopic image color dissimilarities and skin lesion analysis (Akilandasowmya et al., 2024). A computer vision-based machine learning model, k-NN, extracted characteristics and detected, evaluated, and classified pathologic dermoscopic pictures with 99% accuracy (Magdy et al., 2023) Screening Image Super Resolution (ISR) technique was recommended to improve CNN accuracy and achieve higher resolution than Visual LR Image (Lembhe et al., 2023). Pre-Trained Mobile Net Model, a quick, expandable method for dermoscopic analysis, increased diagnostic accuracy by 80% (Agrahari et al., 2022). A Computer-Aided Diagnosis (CAD) model incorporating deep learning techniques, such as the Class Attention Layer and Skin Lesion Classification models, was employed to enhance the detection and analysis of skin lesions based on variations in color and border characteristics. Feature extraction was performed using Capsule Network (Caps-Net), achieving a specificity rate of 99% compared to other approaches (Adla et al., 2022). Computer vision techniques were utilized to assess skin image color, while texture analysis extracted features using the Gray-Level Co-occurrence Matrix (GLCM) and the Gray Level Run Length Matrix (GLRLM). Classification methods were then applied, with the SVM+RF classifier yielding the most accurate results. Convolutional Neural Networks (CNN), which rely heavily on computer vision, demonstrated superior performance in classifying malignant dermoscopic images compared to other neural network models (Dildar et al., 2021). The study also examined the effectiveness of the proposed network and Visual Geometry Group (VGG-19-Deep CNN) models, combined with kernel principal component analysis for texture extraction, in categorizing dermoscopic images. The methodology was tested on ISIC-2016, ISIC-2019, and PH2 databases, where specificity in the PH2 dataset ranged between 96% and 100% (Alizadeh & Mahloojifar, 2021). A deep neural network-based approach was introduced for melanoma and non-melanoma detection using Python, leveraging TensorFlow and Keras beyond standard convolutional layers. The study aimed to identify common skin cancers, including basal cell carcinoma, squamous cell carcinoma, and melanoma. Clustering techniques during segmentation helped differentiate cancer types. A dermoscopic study utilizing the ISIC-2019 dataset achieved 96% accuracy using a multi-class SVM classifier (Monika et al., 2020). Another proposed method applied the Algorithm for Balanced Component Discovery (ABCD) rules for classifying dermoscopic cancer images, following a stepwise process of filtering, segmentation, feature extraction, and weighting to determine cancer type and stage.

This study used PH2 database and got 90% correct findings (Zghal & Derbel, 2020). used CNN and SVM to design a skin lesion image detection model with 85% accuracy (Vijayalakshmi, 2019). Hasan et al. (2019) found 89% accuracy with CNN classifier for dermoscopic image feature categorization after segmentation. distinguished between biopsy-based skin cancer diagnosis and AI-

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based computer-aided diagnosis, which yields better results than biopsy, and computer vision after feature extraction and classification through SVM with Linear Kernel yields the best results (Mane & Shinde, 2018). Described an automated skin lesion classification method using deep and transfer learning applied to Alex Net and replaced with Softmax to identify cancer types in similar dermoscopic skin lesion images. PH2 dataset results showed 98% accuracy and 97% specificity for this technique (Hosny et al., 2018).

METHODOLOGY

Search Study

This study used peer-reviewed articles and research papers on computer vision-AI-based dermal cancer detection. Google Scholar, Springer, Elsevier, and Science Direct were used for this review. To compare Computer Vision-based AI methods for early skin cancer detection through dermoscopic pictures, 14 years of research and reviewed studies (2011-2024) were collected.

Data Extraction & Analysis

This study used published reviewed and original research articles to determine the accuracy and specificity of AI-based Computer Vision algorithms for dermoscopic picture categorization for early skin cancer detection. We compared CNN, ANN, SMV, VGG, k-NN, RNN, and Mobile Networks on accuracy, specificity, and sensitivity using sample sizes from 17 (2011-2024) research.

Methods of Dermoscopic Analysis

For the early detection of various types of dermal cancer, an AI based technique Computer vision aided by following 5 steps, involved in the diagnosis of skin cancer.

Pre-Processing

Most pigmented skin disease studies begin with noise removal. Dermoscopy photographs show air bubbles, black frames, dermoscopic gel, and dermatological characteristics during skin disease study. These defects in dermoscopy images may affect blood vessel, hair, and skin line classification. Such imperfection can make boundary identification difficult, increasing computing costs and decreasing accuracy. Some pre-processing approaches remove undesirable effects to improve identification and segmentation. Many dermoscopy image improvements begin with picture scaling. Many data suppliers supply photos of different dimensions, thus they must all be scaled to the comparable dimension. Preprocessing improves image look, making it necessary. Selecting the right pre-processing steps can boost identification efficiency. Identify and remove everything that could cause tripping during border identification. Researchers use various methods to remove hair (Suja et al., 2023) (Jaworek-Korjakowska & Tadeusiewicz, 2013) (Gururaj et al., 2023; Kiani & Sharafat, 2011), filter (Maglogiannis & Delibasis, 2015), resize images, and quantize color. Working with Red Green Blue (RGB) combinations is difficult due to their millions of permutations. Insufficient image sharpness hindered dermoscopy boundary detection. Skin disease photos are often sharpened to highlight lesion borders (Masood & Al-Jumaily, 2015). Jain & Pise (2015). The scanning process often produces dermoscopic images with dark frames. Several researchers proposed and implemented black frame removal methods. To remove black borders, the Hue Saturation Lightness (HSL) module was used (Zhou et al., 2008). Black pixels are picture pixels with L less than 20. The black frame was found in all image rows. A black frame is defined by the criterion above: a row in the image with a black pixel larger than 60%. Other methods use L smaller than 15 in the literature. If L is less than 15, the picture pixel is black in such experiments. A framework was designed to remove hair and black frames from photos. The dermoscopic image highlights skin and black frames with an ellipse (Sultana et al., 2014). Two hair repair and identification methods are suggested. The partial derivative is used to identify

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hairs, and Exemplar-based painting is used to fix them (Zhou et al., 2008). Greyscale image conversion framework suggested and used. This method uses the blunt mask. Final step used blacktopping hat transformation. The broken borders and hair pixels were replaced with nearby pixels. The testing framework uses 50 and yields 88.7% accuracy (Jaworek-Korjakowska & Tadeusiewicz, 2013). Different dermoscopy hair removal methods were evaluated (Abbas et al., 2011). Another method was based on morphological edge and used first derivative of Gaussian filter on gray scale pictures with comparable filtering to identify hairs in dermoscopy images. This analysis used 100 photos and had 93% accuracy. Integration of dermatology data with computer vision could improve melanoma screening systems. Image segmentation can help diagnose melanoma by recognizing the morphological components of epidermal disorders needed for growth (Abbas et al., 2013).

Genetic Programming (GP), a new Evolutionary Algorithms method, can improve image categorization. The approach used genetic programming to automatically detect skin cancer types. Feature extraction can also use genetic programming. To merge computer vision with dermatology, GP uses domain characteristics from physicians and Local Basic Structure features from morphological pictures. GP can choose excellent characteristics that increase identification effectiveness and a wide variety of approaches for a particular issue, so it could be applied to microscopic images to develop computer algorithms that can efficiently identify malignant images. The framework used Gabor wavelet and morphological methods for hair removal and dermoscopy picture preparation (Jamil & Khalid, 2015). First, hairs were identified, then the image was rebuilt using extrapolation. Log Sobel and Both are built methodologies. Lack of picture testing is a downside of the proposed strategy. This analysis created light brown, dark brown, and black images (Maglogiannis & Delibasis, 2015). Comparison of pre-processing-based analyses was presented. Tajeddin & Asl (2016) developed methods to automatically extract sick skin from images. A skin disease categorization method was suggested for a wide variety of images with different characteristics and abnormalities. Multiple hair removal preprocessing methods exist. After these implementations, a thresholding factor-based technique is used to detect the lesion in the image. The initial mask samples lesion pigment and drives contouring proliferation. The original mask captured tumor color and controlled contouring propagation. Image color likelihood maps are constructed using Bayesian categorization of observed images. This probability map with picture gradient is used to develop a novel dual constituent speed technique to improve propagation classification. Testing and evaluation of the proposed framework are done on the ISIC dataset. This dataset contains 900 photos (Pathan et al., 2018). The framework was developed to automatically extract lesion and hair from the image using lesion attributes for successful results. The technique first examines how hairs are recognized from the dermoscopic image, then develops a Chroma-based geometric model to identify skin lesions. All tumor chrominance features are integrated by the speed factor to stop development near the tumor margin. Initial Contour and Speed function determine segmentation effectiveness. The proposed architecture is tested using PH2 and ISBI datasets. PH2 has 200 pictures, ISBI 900. The PH2 dataset has 93.4% accuracy and ISBI dataset 94.6% (Mane & Shinde, 2018). A skin cancer detection method including pre-processing, picture segmentation, and feature extraction was suggested. In this investigation, picture segmentation follows pre-processing to eliminate noise. In picture segmentation, healthy skin is separated from lesions. The final stage extracts visual features using form and color. Support vector machines are trained using extracted features to classify images as melanoma or normal skin cancer. This analysis uses linear kernel in the Support Vector Machine (SVM) to get 92% reliable findings (Arasi et al., 2016). Another algorithm given for dermoscopic imagery hair removal. The Wiener filter removes image noise in the described method. After distinguishing bright and dark hairs with adaptive Canny edge, morphological operations were done. The previously mentioned methodologies were created and utilized to simplify categorization and feature collecting, improving analytical results (Toossi et al., 2013).

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Segmentation

Image segmentation plays a crucial role in distinguishing the affected region from the rest of the image, as illustrated in Fig. 3. A skin image consists of both healthy and lesion areas, and processing both components simultaneously can reduce classification accuracy. For effective analysis, segmentation focuses solely on isolating the lesion. Some studies suggest that manually detecting lesion borders is quicker and often produces more accurate results compared to automated systems (Rodrigues et al., 2020). However, computerized segmentation algorithms are essential for automated skin cancer detection. Researchers have developed various segmentation techniques, which can be classified based on different methodological approaches. Figure 2 presents an overview of these segmentation methods.

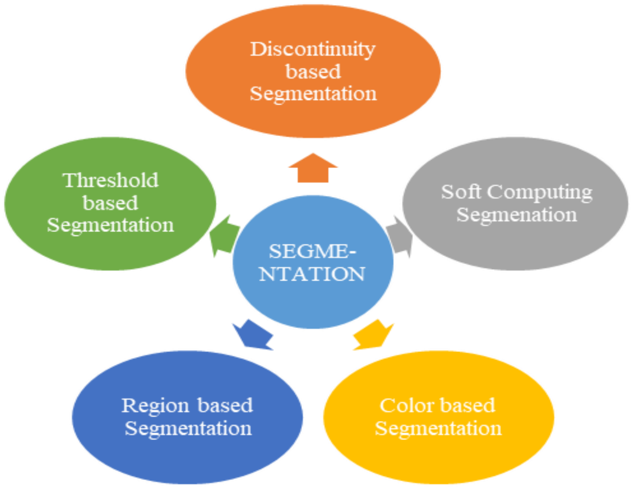

Figure 2: Segmentation Techniques

The first segmentation method divides images into groups based on a given threshold (Lingala et al., 2014). Color selection dominates color-based segmentation (Kiani & Sharafat, 2011). Discontinuity-based segmentation uses radial search and active contour to detect picture edges. Region-based segmentation is another type of segmentation. This segmentation breaks photos into little pieces. Adjacency is used to blend these image components. The computing-based segmentation method uses fuzzy logic approaches.

Feature Extraction & Classification

Feature extraction extracts unique qualities from an image. Features in the photograph would convey its traits. That stage is crucial. Melanoma epidermis images vary in hue, whereas benign tumors are consistent. Benign lesions are circular, while melanoma is asymmetrical. This method would derive pigment, border, size, inconsistency, and surface properties from the epidermis image. The classification of malignant and benign skin cancer depends on skin features. Different studies extract contour, texture, color, and histogram information from skin photos (Hameed et al., 2016). Color is crucial to skin disease diagnosis. Color can identify pigmented skin if analyzed correctly. Color distribution is another indicator of pigmented skin. Both are key dermoscopy picture evaluation elements. The skin appears white under a microscope. Melanin pigment helps identify architectural and color features. Pigmentation depends on melanin deposition across skin tissues because the skin has several layers (Tsao et al., 2015). Different hues indicate tumor status. Light Brown injunction, Black in external skin, steel Blue and slate Blue in reticular and papillary tissue. White and red tones can vary in intensity. Red tones are often connected with increased malignancy vascularization, lesion bleeding, and blood artery volume. If bleeding increased, tissues turned black from red and blue.

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Various color models are utilized in melanoma screening, with RGB, HSL, and HSV being the most commonly applied. The feature set, often referred to as ABCD, includes asymmetry (A), border irregularity (B), color variation (C), and diameter (D). Additionally, statistical measures such as mean value and standard deviation assist in skin cancer identification. Figure 3 illustrates the steps involved in predicting skin cancer.

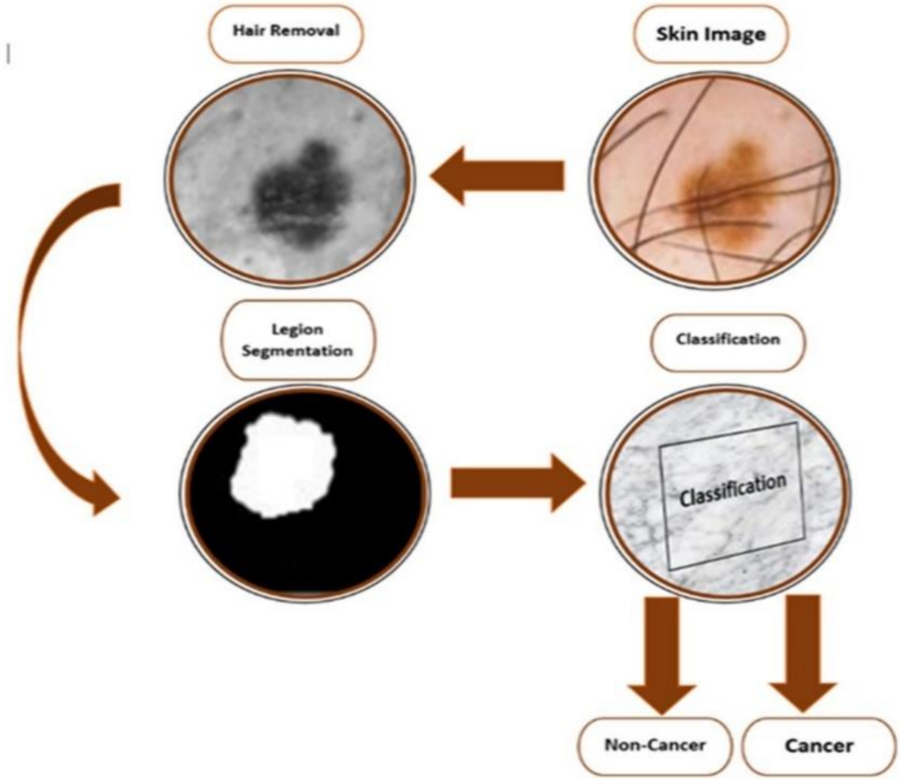

Figure 3: Skin cancer Classification steps

In the classification stage of detection technology, conclusions are drawn based on analyzed data. Various classification techniques have been explored in the literature, with some methods being computer-aided and others relying on clinical evaluation. Among the widely used classification approaches are computer-aided techniques, Menzies criteria, and the ABCD rule. Many studies have leveraged machine learning, deep learning, and computer vision to facilitate the automatic detection of skin cancer (Bi et al., 2017; Majumder et al., 2019; Xie et al., 2016; Talavera-Martinez et al., 2020).

Commonly utilized classification algorithms include K-nearest neighbor (KNN), support vector machine (SVM), decision trees, and artificial neural networks. In statistical research, both learning models and evaluation metrics play a crucial role in assessing performance.

Training and testing sets are key in such networks. Two data sets must be very different. Machine learning and deep learning networks use training sets to train and testing sets to evaluate models. We can evaluate the model using two parameters. Specificity and Sensitivity (Kalouche et al., 2016). Some models' accuracy is calculated using machine learning and computer vision-based equipment. Developing such a tool helps doctors and patients detect malignant or benign skin cancer. That method yields accurate results using a cell phone camera. The ISIC database yielded 1280 samples. Noise prevents the Neural network from training on these photos. Before training the neural network, the dataset is cleaned and preprocessed to accurately classify skin cancer. Noise-filled datasets cannot produce reliable findings. Preprocessing removes noise without affecting neural network

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performance. This analysis uses three models to improve categorization. First is Logistic Regression, then VGG-16, and finally a pre-tuned CNN. Using the VGG-16 network yields 78% accuracy. The suggested approach predicts skin lesions using picture segmentation and classification (Srinivasan & Srinivasan, 2020). The Convolutional Neural Network-based approach was presented. This CNN network study classifies cancer using clinical data. Keeping false-negative rates below 10% will help create a CNN with accuracy over 80%. This analysis visualizes the dataset for precision over 80%. The suggested network predicted skin cancer well due to neural network learning. This analysis uses HAM 10000. A big collection of dermoscopic images. This dataset contains pigmented skin lesions. The HAM dataset has 10015 samples. All photos in this study are 600 x 450. To determine model effectiveness, the test set is used. CNN has 80% accuracy in this analysis. The model has the same accuracy when trained with randomly selected photos from the dataset (Adegun & Viriri, 2021). System performance was assessed using various metrics. These characteristics were recall, precision, and accuracy. A framework was created to detect skin cancer. Machine learning and computer vision are used in that framework. This framework helps anyone detect skin cancer quickly and get treatment. Unlike CT scans and MRIs, that approach is available to hospitals and allows for fast, low-cost diagnosis. CT scans are Computing Tomography scans while MRIs are Magnetic Resonance Images. This analysis combines object detection with convolutional neural network ensemble. The GUI detects skin lesions. The user can easily upload the skin lesion video in such GUI. System automatically extracts skin cancer image. The proposed technique automatically offers cure and medical source after cancer identification. The given system helps in areas with minimal diagnostic tools. The CNN model is trained using 10015 dermoscopic pictures from the HAM dataset. The framework has 87% accuracy. All dataset images are 650 × 400 x 3 and belong to seven classes (Lynn & Kyu, 2017). Successful methods for identifying Melanoma using skin lesion photographs. A survey is provided to help academics build algorithms to swiftly and efficiently diagnose malignancy using skin lesion photographs.

This study examines challenges in melanoma detection, emphasizing segmentation, preprocessing, and classification techniques (Attia et al., 2017). Deep learning models outperform traditional methods, particularly when applied to segmented and preprocessed images. Preprocessing removes noise and unwanted features, while segmentation isolates the lesion for improved classification. The ABCD method extracts features based on asymmetry, border irregularities, color variations, and diameter, optimizing feature selection for machine learning models such as SVM, KNN, and Decision Trees (Cueva et al., 2017).

A hybrid deep learning approach using CNNs and RNNs was tested on the ISBI dataset, achieving 98% segmentation accuracy. Compared with other ISBI-based techniques, this method effectively addressed melanoma detection challenges without requiring dimension reduction or additional preprocessing (Junayed et al., 2021). Another approach employed deep learning and encoding techniques to classify dermoscopic images, integrating residual neural networks with feature encoding for enhanced melanoma detection (Bi et al., 2017).

The study evaluated various CNN-based models, including ResNet-50 and ResNet-101, trained on the ISBI dataset, which consists of 1,279 images (Mane & Shinde, 2018). CNNs were found to be highly effective due to their ability to automatically extract and classify lesion features. Using the ABCD framework, models analyzed parameters such as lesion shape, border clarity, and color variations, achieving 97.51% accuracy in classifying malignant and benign cases.

Deep learning methods consistently outperformed traditional machine learning techniques. CNN models trained on large datasets, including 3,297 dermoscopic images, showed superior accuracy, specificity, and sensitivity (Vidya & Karki, 2020). A mobile application employing a CNN framework facilitated real-time melanoma detection, making diagnosis more accessible. The use of augmented datasets ensured model robustness across varying image sizes and sources (Dai et al., 2019).

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This research highlights the effectiveness of AI-driven methods in skin cancer detection. The integration of CNNs, SVMs, and ANN models, tested on datasets such as ISIC and PH2, demonstrated high classification accuracy. The CNN-based model achieved 95.98% accuracy, outperforming MobileNet and GoogleNet (Wadhawan et al., 2011). Additionally, machine learning models applied to the PH2 dataset achieved 92.5% accuracy with ANN, 89.5% with SVM, and 90% with KNN (Ramlakhan & Shang, 2011). These findings confirm that deep learning models offer reliable and efficient tools for early melanoma detection, potentially improving patient outcomes.

Smartphone-Based Skin Cancer Detection

With advancements in mobile technology, smartphones are increasingly used in healthcare, particularly for skin cancer detection. Equipped with high-resolution cameras and powerful processors, they support medical applications. However, many skin cancer screening apps are designed for iOS, making them less accessible in developing regions due to cost (Kalouche et al., 2016; Srinivasan & Srinivasan, 2020). Additionally, some apps lack accuracy, and those that rely on dermatologist evaluations cause delays, making them less effective for remote users (Suja et al., 2023).

To address these challenges, researchers are developing smartphone-based automated diagnosis systems. A study using 2D median filtering and an SVM classifier achieved 85.57% specificity and 80.76% sensitivity on 1,300 images (Adegun & Viriri, 2021). Another approach used ISO-DATA segmentation and k-means clustering, with SVM classification yielding 71.31% specificity and 87.27% sensitivity on 340 images (Wadhawan et al., 2011).

Other models applied greyscale conversion and K-NN classification, achieving 66.7% efficiency (Lynn & Kyu, 2017). A cloud-based system for mole classification into melanoma, nevus, or benign lesions integrated AES encryption and WEKA-based classification, scoring 75 for accessibility and 80 for effectiveness (Attia et al., 2017). The DERMA/Care iOS app utilized microscopes for image acquisition and SVM classification, successfully identifying tumors in 12 test cases (Cueva et al., 2017).

A deep learning-based smartphone system applied a multilayer perceptron, resizing images to 32×32 pixels for efficient processing, making it suitable for rural users without access to specialists (Cueva et al., 2017). Another study combined Otsu's method with a minimum spanning tree for segmentation, using SVM classification on optimized features (Junayed et al., 2021).

A two-part real-time smartphone system integrated UV exposure alerts and automated skin lesion diagnosis. Trained on the PH2 dataset, it classified lesions as benign (96.3% accuracy), atypical (95.7%), and melanoma (97.5%), demonstrating high efficiency in mobile-based diagnosis (Pedro Hispano Hospital, PH2 database).

RESULTS

To improve dermoscopic analysis and classification accuracy, sensitivity, and specificity, computer vision-based methods were examined. CNN with RNN had 98% accuracy with sample size 1275, CNN with 97.51% with 200, SMV with 97.8% accuracy 1000, mobile networks with 95% accuracy 10015, and ANN with 92% accuracy 200.

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Table 1: Comparison between various techniques

Year	Study	Sample	Technique	Accuracy	Specificity	Sensitivity	Recall	F-Score	Precision
20		1280	VGG-16	78%					
21		10015	CNN	80%			80%	82%	81%
17		10015	CNN	87%					
17		240	SVM, KNN, Decision tree	76%, 71%, 76%					
21		1275	CNN+RNN	98%					
17		1279	Resent-50 & Resent-151	N/A					
19		200	CNN	97.51%					
20		3297	CNN	84.76%	84.56%	78.71%			
19		800	CNN	95.98%					
17		10015	Mobile net	95%					
15		23907	CNN	93.7%					
15		1000	SVM	97.8%	85%	86.2%			
11		10015	CNN	N/A					
11		200	ANN, SVM, KNN	92.50%, 89.50%, 90.0%					
24		-	SVM+NN	86%					
23		-	VGG+ISR	70.17%					
22		-	Pre-Trained Mobile Net	80%					

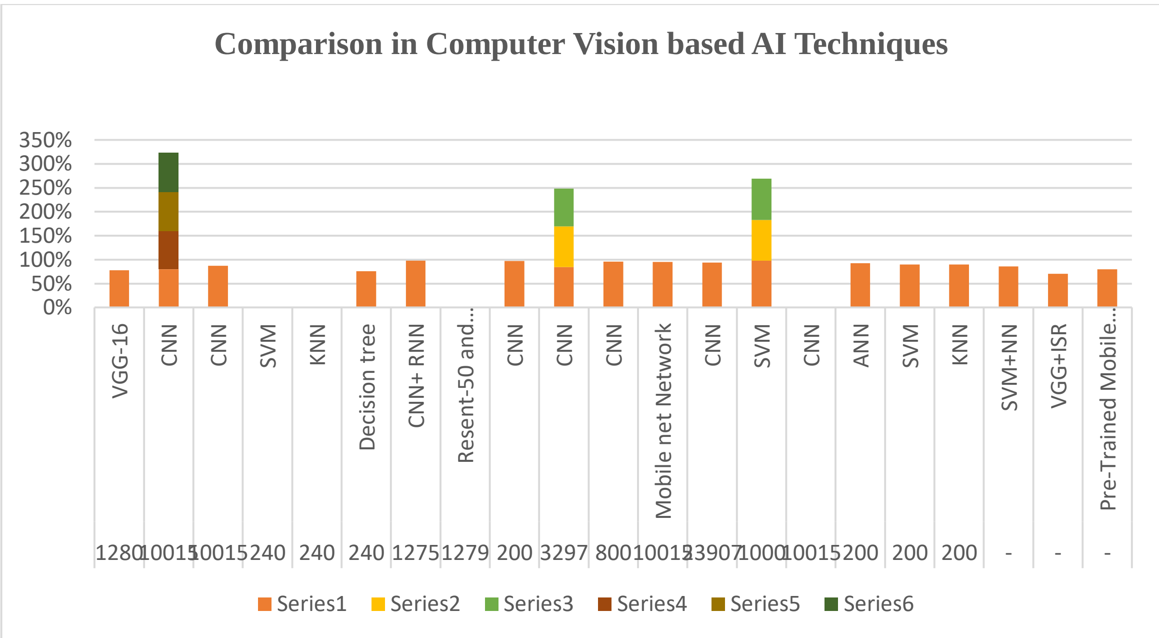

Figure 4: Comparison in Computer Vision based AI Techniques

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DISSCUSION

Prolonged exposure to UVA and UVB radiation, along with genetic mutations, can lead to skin cancer, one of the most common types of cancer. Skin cancer is broadly categorized into melanoma and non-melanoma types. Non-melanoma skin cancers include basal cell carcinoma and squamous cell carcinoma, which occur more frequently than melanoma. Melanoma develops due to abnormal melanocyte activity, leading to excessive melanin production. Early detection is essential to prevent its progression into a malignant tumor, increasing survival rates and reducing the risk of spreading to other body parts.

Advancements in technology have introduced AI-driven skin cancer detection systems that offer greater accuracy compared to traditional diagnostic methods such as biopsy, computed tomography (CT), and magnetic resonance imaging (MRI), which can be time-consuming and costly. This study explores computer vision techniques and AI-based classification methods for dermoscopic images, evaluating their accuracy, specificity, and sensitivity. The process begins with image filtering, followed by segmentation and feature extraction to improve diagnostic precision. Computer vision assists in detecting skin cancer early by analyzing pigmentation patterns. For effective dermoscopic image processing, artifacts such as noise, air bubbles, black frames, and other non-essential dermal features must be removed while ensuring uniform scaling of dimensions.

After filtering, segmentation isolates the lesion area from healthy skin, allowing for more precise feature extraction. This review compares various machine learning models, including Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), k-Nearest Neighbors (k-NN), Recurrent Neural Networks (RNN), Support Vector Machines (SVM), Visual Geometry Group (VGG), Decision Trees, and Mobile Networks to determine the most effective tool for analyzing dermoscopic images. The comparison of these approaches across different population samples indicates that CNN and RNN achieved 98% accuracy, outperforming other models. A standalone CNN model demonstrated 97% accuracy, proving to be highly effective. SVM classifiers efficiently handled complex data, while mobile networks achieved 95% accuracy, making them a practical option for individuals in rural areas where access to expensive skin lesion diagnostics is limited. Among the models, ANN exhibited higher accuracy than k-NN, CNN, and SVM.

Research Challenges

In computerized Melanoma tumor detection technology, various investigation concerns must be addressed. Furthermore, during image pre-processing, the investigator must focus on removing disturbances in a key area. There are noise filtering methods, but results are disappointing. Further research is needed to improve tumor surface detection accuracy and address elements such as processing efficiency and fluency while developing automated methods for separation. Selecting the correct classifier features is another difficulty. Epidermal tumors have many characteristics, but determining the fewest that offer the best results in reliability, complexity, calculation effort, and effectiveness is tough. Because cell devices have limited storage and processing capability, building a classifications approach for a mobile-based melanoma tumor detection method that provides real-time results with better efficiency is difficult.

CONCLUSION

Early skin cancer detection reduces mortality, according to this study. This paper highlights computer-based framework improvements and prior studies in skin cancer diagnosis computer system steps. Previously described systems use different preprocessing, feature retrieval, and segmentation methods. Lesion regions can be identified from dermatological photos using the attributes. After reviewing the literature, particular results were found and examined. There are many machine

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learning approaches used to cure skin cancer, however SVM is the most effective at 60%-98%. Smartphone skin cancer therapy solutions are equally effective. A Smartphone-based cancer detection system runs in seconds, which is the typical duration on any Smartphone platform, according to previous research. This review showed validated and trained work on several datasets. Because dataset size and image properties vary, paper evaluation is problematic. Regularized processes and readily accessible datasets should be available to new researchers. These methods will help us survive this perilous condition. Real-time classification, noise removal, and segmentation in smartphone-based skin cancer therapy systems are popular literature topics.

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