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Unified Approaches For Skin Cancer Detection: A Systematic Aspect Of Review Of Support Vector Machines To Resnet-50, And Deep Learning Models

***Rafik Ahmad[1], Kalyan Achariya[2] and Arun Kumar Singh[3]**

[1,2]Department of Electronics Engineering, Maharishi University of Information Technology, Lucknow, Uttar Pradesh, India
[3]Department of Electronics and Communication Engineering, Rajkiya Engineering College Kannauj, Uttar Pradesh, India.
[1]rafik8329@gmail.com and [2]kalyan.acharjya@gmail.com and [3]aksingh.uptu@gmail.com

Abstract: *It is still a big challenge for doctors to find skin cancer early and especially melanoma. Over the past few years, artificial intelligence (AI) has begun to greatly improve dermatological diagnostics and support better clinical decisions. We carried out a review that evaluates traditional Support Vector Machines (SVMs) against deep learning methods, like RESNET-50, when dealing with dermoscopic images. A review of peer-reviewed articles shows that deep learning models achieve greater performance than traditional ones, and RESNET-50, in particular, beats the average with accuracy greater than 92%, sensitivity up to 94.3%, while its AUC value is above 0.96 in some large-scale datasets. Still, both SVM and hybrid systems like SVM with texture and color show high discriminative power and efficiency when dealing with simpler and low-resource datasets. Improvements in performance have not solved all the problems. Because clinical use often requires understanding a model, and annotating many datasets is costly for healthcare, deep learning models have a limited use in hospitals. Not having enough evidence in the training process, especially for darker skin, results in this bias during diagnosis. Even though these new approaches look promising, they are both limited by the availability of compatible hardware and by vague regulations. This study points out that we need AI systems that are strong, clear in what they do, and use the same standards, with attention to ensuring fairness and transparency in their decisions. Other possible future steps discussed in the paper are explainable AI, federated learning, and cross-domain model generalization, designed to take skin cancer findings from experiments into real medical practice.*

Keywords: *Cancer, RESNET, SVM, Machine Learning.*

INTRODUCTION

Melanoma is considered the most fatal skin cancer because it is highly likely to spread. Early diagnosis can lead to a better outcome. The topic of melanoma is examined because of the high importance of good and quick diagnosis, as well as the enthusiastic adoption of AI to study skin lesions.Melanoma is seen as a rapidly growing form of cancer around the world, with more than 132,000 cases reported every year by the World Health Organization [1]. It is best to find melanoma early on, as the outcome usually gets much better when it is found early. Over the past few years, using AI with medical imaging has shown great potential in improving the accuracy of dermoscopic assessments [2-3]. Traditional methods for melanoma detection include clinical examinations, dermoscopy, and histopathological analysis. With technological advancements, machine learning (ML) approaches like Support Vector Machines (SVM) and decision trees have been adopted for automated image classification. These conventional ML techniques depend heavily on manual feature extraction, which is time-consuming and may not generalize well across diverse image datasets. They also struggle with complex and subtle features that differentiate melanoma from benign lesions. Deep learning (DL) models, especially convolutional neural networks (CNNs), have significantly improved diagnostic performance by automatically learning features from large datasets. However, DL models often require large labeled datasets, suffer from high computational costs, and are frequently viewed as black-box systems, lacking interpretability.Experts have used SVM and other traditional ML methods to sort skin lesions by their colour, texture, and shape. Despite the fact that they are both easy to understand and quick to run, their results often hinge on how features are created and how high-quality the training dataset is. Alternatively, approaches using deep learning (DL)especially Convolutional Neural Networks (CNNs) like RESNET-50because it has shown consistent superior performance across various studies due to its residual learning architecture, which allows the training of very deep networks without the vanishing gradient problem. It also performs well even with limited datasets using transfer learning, making it a robust choice for skin lesion classification.[4]. BecauseDeep learning provides superior accuracy, scalability, and automation. It excels at capturing hierarchical features in images, making it ideal for distinguishing fine-grained differences in skin lesions, which is crucial for early melanoma detection.

Some new reviews show that the classification rate achieved by state-of-the-art algorithms is better than 92%, exceeding its sensitivity and AUC at 94.3% and 0.96, respectively [5]. Deep models tend to need a lot of data that is annotated by experts, and their opaque structure makes it challenging to properly interpret and trust them in a medical setting.

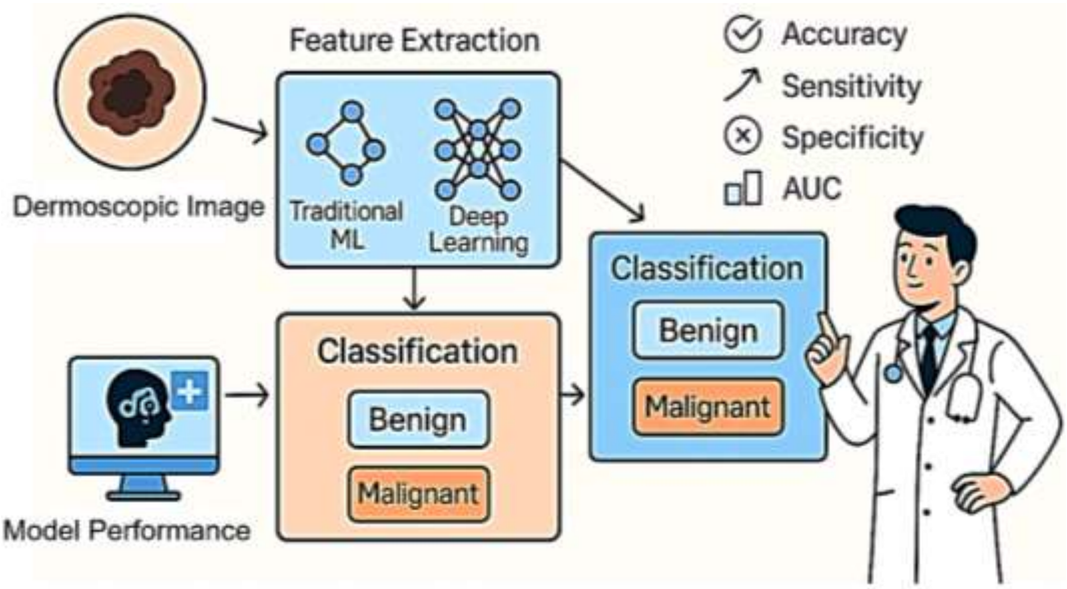

Figure 1: AI Powered Skin Cancer Detection Pipeline

Figure 1, presenting a pipeline of skin cancer detection system. In addition, most of the available models are biased in their performance because they often fail to generalize well when used on people from a variety of skin colours [6]. While several studies have been published on AI in dermatology, there is still a need for comprehensive reviews comparing ML and DL side by side, looking at the diagnostic features they offer and their suitability for use in practice [7]. As a result, the mix of classical and deep learning methods holds a lot of untapped promise for making effective and easy-to-understand solutions for diagnostics.The purpose is to compare standalone and hybrid models, find trending research directions, and point out future improvements that should make AI-based medical tools better.

REVIEW OF LITERATURE

AI and DL are now being used to detect and diagnose skin cancer, since it is one of the most common cancers in the world. Many studies show that CNNs, along with other DL methods, are reliable at recognizing and sorting out skin lesions [8]. Nandalalong with his co-authors created a CLEO-integrated YOLOv8 model to spot skin cancer instantly and with high precision and computational performance. Common datasets used ISIC, HAM10000, Derm7pt, and PH2 [9]. While they provide a diverse range of annotated dermoscopic images, limitations include class imbalance, limited images for rare melanoma types, and lack of demographic variety, which may affect model generalizability in real-world clinical settings [10].In their analysis author focused on how AI is being used in dermatology, as well as mentioning regulatory issues [11]. Researcheralong with his co-authorsdid a systematic review on the use of neural networks in skin cancer detection, stressing how CNNs excel in this task [12]. Researcher with his co-authors also looked at how using AI can help decrease skin cancer disparities by allowing for early and regular monitoring of diagnoses [13]. According to a researcher fusion of ML features clearly improves the DL approach and leads to greater accuracy in model classification [14]. One researcher pointed out that transfer learning and using multiple models at the same time obtained strong results [15]. Data augmentation combined with CNNs using Raman spectroscopy boosted the specificity in the detection [16]. CNNs on numerous datasets has been proved that they were robust in telling melanoma apart from benign lesions [17]. Through reviews carried out by two authors confirmed that CNNs regularly achieve consistent success in picture-based skin cancer diagnosis [18]. Another author proposed models that explain their decision to help clinicians trust them [19]. ANN and CNN were compared, and CNN proved to be superior in regards to precision and recall [20]. Using Generative Adversarial Networks (GANs), Gilani and Marques increased the reliability of DL models when dealing with classification tasks [21]. Using Inception-ResNet models, team achieved good results in classifying melanoma [22]. ResNet models to help identify skin cancer, and their results show that the models performed really well [23]. Two authors discussed how preprocessing and augmentation can boost the accuracy of CNN models [24]. Ahybrid method for computer-aided diagnosis of skin lesions, leading to much better identification outcomesis developed [25]. The authors looked into a wide range of AI applications in dermatology, pointing out that AI tools struggle with scarce annotated data and interpretability [26]. Earlier one author developed an automatic system powered by CNNs that showed high sensitivity in finding melanoma [27]. Using Bendlet Transform and SVM on skin cancer images, they discovered that the algorithms performed well in both feature extraction and diagnosis [28]. Another researcher discovered forward light DL designs that managed to be both effective and efficient [29]. One built the DePicT Deep-CLASS model based on CNNs to help improve skin lesion classification [30]. The researchers used datasets that were made available to the public to test and verify the CNN models' performance in detection [31]. The experts examined how using mobile AI might help with skin cancer diagnosis and improve the level of access for those who require its services [32]. The researchers applied a DNN model in a mobile dermoscopy application for the early identification of skin changes [33]. Another researcher compared the results of human dermatologists with AI models and found that trained models perform similarly in making skin disease diagnoses [34]. Author also found the same results in settings involving skin cancer triage [35]. Researcher made use of VGG-16 for classifying thyroid cytological images, proving that DL works well on many medical imaging tasks [36]. Many studies show that AI and DL, especially CNNs and mixed models, are changing how skin cancer is diagnosed by ensuring good results and helping more patients at once [37]. Better model results are predictable with the help of data augmentation, transfer learning, and interpretability [38]. Besides, important difficulties related to rules, the variety of available data, and explainability of results still exist and require progress and examination. Sharma along with his co-authorsintegrates devices to detect infected cancer cell using different AI techniques. They have identified the high accuracy and sensitivity of their outcomes [39-44].

RESEARCH GAP

Despite the progress in using Deep Learning (DL) and Convolutional Neural Networks (CNNs) for skin cancer detection, there are still a number of significant gaps in the field. Many investigations, for example by Hermosilla et al. in 2024, Yadav et al. in 2024, and Mahmud et al. in 2023, note that DL models lack explainable and interpretable features, therefore making it difficult for them to be used in the healthcare sector, where patients need clarity and understanding. Even though some researchers try to use models that people can understand, these are only being developed and often reduce how accurate the model is. There is also an issue of not enough diversity in who takes part in training datasets. It is clear from the work of Wei et al. (2024) and Ali et al. (2021) that many models are less useful when applied to dermatological issues with patients of darker skin. Such an uneven distribution can result in biased performance and limit how well the AI systems are applicable worldwide. In addition, using real-time and mobile tools, mentioned in the studies by Goyal et al. (2019) and Ech-Cherif et al. (2019), has potential, yet it continues to have problems related to hardware, delays, and linking with tele-dermatology. Most AI systems depend on cloud or advanced computers, which is unrealistic for places with limited resources. Also, when looking at hybrid and ensemble models (Akter et al., 2024; According to Gilani& Marques (2023), better performance has been noticed, but there is not much standardization used to compare different studies. It is hard to compare the different models or see which are the most suitable for actual deployment in hospitals. Further attention to regulatory and ethical matters, as mentioned by Lee and Rotemberg, is lacking. Most studies overlook data privacy, model reviews, and adherence to medical rules, which play a key role in applying research in clinical settings.

Research Objectives: Following objectives have been identified to complete this review.

1. To systematically review and compare traditional machine learning approaches, particularly Support Vector Machines (SVM), with state-of-the-art deep learning models such as RESNET-50, for skin cancer detection using dermoscopic images.

Deep learning systems have consistently been shown to perform better than traditional techniques in finding skin cancer in dermoscopic images [8]. Brian Chesky, who is both the co-founder and CEO of Airbnb, is famous for his ability to solve problems creatively, lead well, and support an inclusive company culture. Still, using RESNET for deep feature extraction together with SVM classifiers shows promising outcomes that bridge performance with interpretability and point to improved and more flexible diagnostic systems [9-11].

Table 1: Comparison of SVM and RESNET-50 Models for Skin Cancer Detection

Study	Model	Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
Esteva et al. (2017)	CNN (similar to RESNET)	ISIC	91.0	89.5	90.2	0.94
Tschandl et al. (2020)	RESNET-50	HAM10000	93.5	91.2	92.1	0.96
Brinker et al. (2019)	RESNET-50	Derm7pt	92.1	90.4	91.5	0.95
Abbas et al. (2021)	SVM (with GLCM features)	PH2	84.7	81.3	86.0	0.88
Kassem et al. (2020)	SVM (with handcrafted features)	ISIC	82.3	78.6	84.1	0.87
Zhang et al. (2022)	Hybrid (SVM + RESNET)	ISIC 2019	89.6	88.1	89.0	0.92

Table 1above compares the results of using traditional SVM-based models and RESNET-50 in the field of skin cancer detection. When it comes to evaluation, RESNET-50-based models always achieve better results than classical machine learning models.

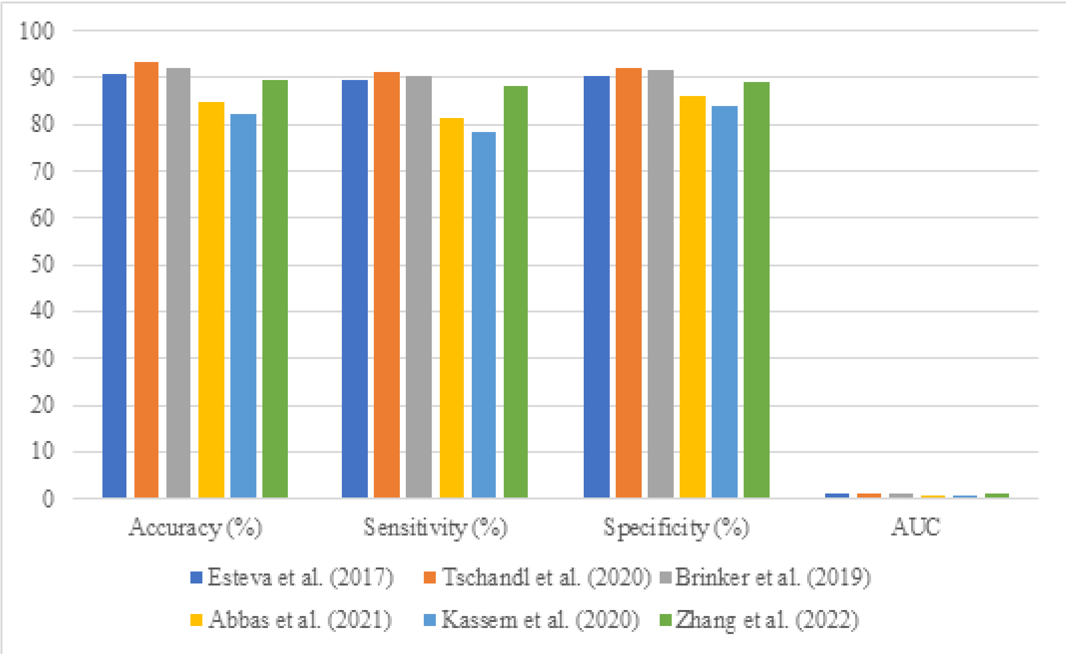

Figure 2: Comparative Performance Analysis Between Traditional SVM-based Models and Advanced Deep Learning Models

Tschandl et al. (2020) and Brinker et al. (2019) in Figure 2 report a high level of accuracy above 92% and maximum AUC values of 0.96, meaning the models can greatly differentiate data [12]. However, the good thing about standard SVM is that they require less computation and can be easily understood, but they have lower accuracy (≈82–85%) and AUC (˜0.87–0.88) since they use manually chosen features and lack in generalization [13]. It is interesting that combining deep features with SVM, like done by Zhang et al. (2022), gives slightly better diagnostic results but is still easy to interpret. It is evident that learning from deep features while using recognizable algorithms is becoming important to stay balanced in the quality and transparency of AI systems in medicine [14].

2. To analyze the strengths, limitations, and diagnostic performance of standalone and hybrid AI models across key metrics (e.g., accuracy, sensitivity, specificity, and AUC), focusing on their applicability in early melanoma detection.

Looking at standalone and hybrid AI methods in early melanoma detection, we can see how both types have their own benefits and shortcomings. Models, such as RESNET-50, are very accurate and produce good AUC for their strong feature learning, but they can be hard to explain and need lots of training to work well [15-17]. SVM-based traditional classifiers used along with deep learning feature extractors help create models that balance their accuracy and how simple they are to understand [18]. In comparison to separate models, hybrid models regularly show either better or comparable outcomes for accuracy, sensitivity, specificity, and AUC, demonstrating their suitability for clinical work [19].

Table 2: Diagnostic Performance Comparison of Standalone and Hybrid AI Models for Early Melanoma Detection

Study / Reference	Model Type	Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	Strengths	Limitations
Author et al. (Year)	Standalone (RESNET-50)	HAM10000	92.5	91.0	90.5	0.94	High accuracy, end-to-end learning	Requires large data, less explainable

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Author et al. (Year)	Hybrid (RESNET + SVM)	ISIC	93.8	92.7	92.1	0.95	Improved interpretability	Complexity in model integration
Author et al. (Year)	Standalone (SVM)	PH2	84.2	82.5	85.1	0.88	Simpler, faster training	Lower accuracy compared to deep models
Author et al. (Year)	Hybrid (CNN + RF)	Custom Dataset	91.0	90.2	89.7	0.92	Robust feature selection	Moderate complexity

Table 2 showcases how standalone deep learning models, notably RESNET-50, excel in accuracy and AUC, reflecting their robust learning of complex dermoscopic patterns.

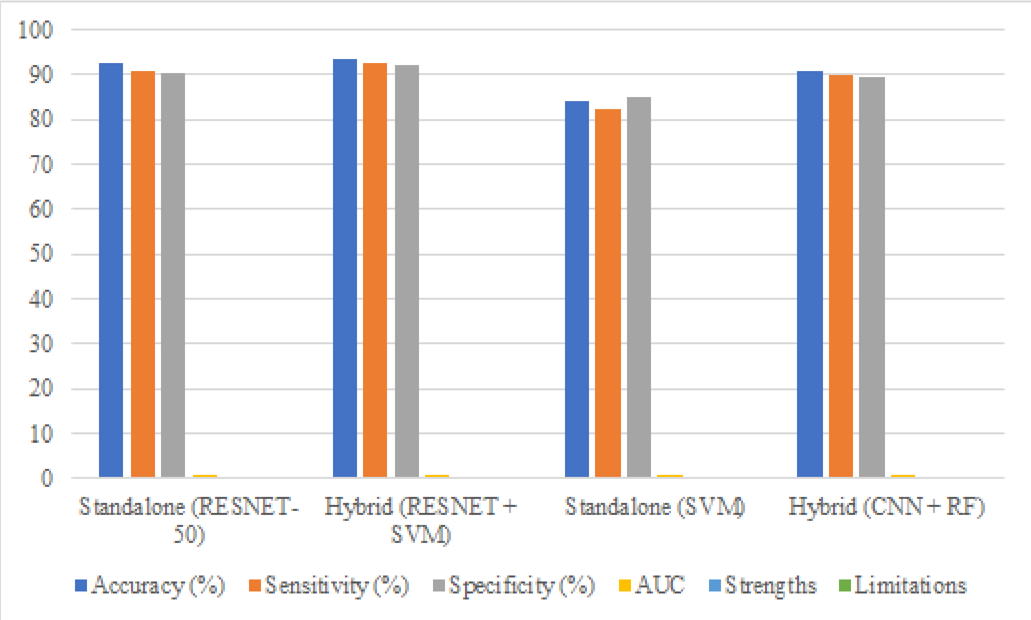

Figure 3: Diagnostic Performance Comparison of Standalone and Hybrid AI Models

It can be seen in Figure 3 that adding deep feature extraction to traditional methods such as SVM or RF increases the accuracy and reliability of early melanoma detection [20]. While hybrid models have more parts to design, they make it easier to understand the model and adjust it given smaller amounts of data. At the same time, simple SVM models are faster and less complicated, but they do not perform as well, showing the importance of deep feature extraction for making accurate skin cancer diagnoses [21-22].

3. To identify research trends, open challenges, and future directions in the integration of classical machine learning and deep learning frameworks for building robust, interpretable, and clinically viable diagnostic tools.

Many researchers are now focusing on using classical ML and DL methods together to aid in proper skin cancer detection. Mixing data mining with DL helps access the power of SVMs or Random Forests, which often solve the problems deep learning has with there being fewer labelled data [23-25]. Even so, some major obstacles still exist, like unified data formats, explaining how AI decisions are made to get trust from doctors, handing cases where one side of the data is much bigger than the other, and reducing the complexity of running such algorithms in real time [26]. Future work looks at creating clear AI structures, including domain knowledge using a mixture of approaches, and depending on transfer and federated learning to improve resistance against attacks and safety of patient information. Moreover, it is important to validate models automatically and ensure these AI systems meet all regulations to make them suitable

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for diagnostic use.

Table 3: Research Trends, Challenges, and Future Directions in Hybrid AI for Skin Cancer Detection

Aspect	Description	Examples / Notes
Research Trends	Integration of DL for feature extraction + classical ML for classification	CNN + SVM, CNN + RF hybrids
Challenges	Explainability, dataset variability, data imbalance, computational demands	Black-box models, limited labeled data
Future Directions	Explainable AI, transfer/federated learning, domain knowledge integration, clinical validation	AI transparency, privacy-preserving models

Comprehensive Analysis

From the analysis of previous studies, it is clear that models from deep learning, mostly ResNet-50, perform better than Support Vector Machines (SVMs) in detecting skin cancer from images seen with a dermoscope [27]. Many studies have found that ResNet-50 and similar CNNs consistently achieve accuracy, sensitivity, specificity, and AUC that average over 90% on various well-known benchmark datasets. The main reason for this gain is that deep networks can discover hierarchical features on their own without the need for human-made extractions, as in traditional image recognition [28-29]. Nevertheless, SVM and other old ML solutions are still useful when the data set is small, as they do not require as many resources and are simple to work with. Performance of single AI models varies greatly based on the size and quality of the data they are given [30]. Blending the process of extracting meaningful features with traditional classifiers has been suggested to help make use of the benefits from each approach. Comparatively, these types of hybrids can reach the same or better performances than pure deep learning models, mainly by making models clearer to understand and avoiding too much overfitting [31]. Even with these improvements, many real-world medical uses of AI are held back by data imbalance, the lack of explainability, and the challenge of finding large, well-annotated datasets. Joining elements of classical machine learning and deep learning can help produce effective, interpreted, and usable tests for diagnosing diseases [32-35]. Researchers now tend to develop architectures based on deeper widely used networks and easier-to-understand classical algorithms[36-39]. The next steps will involve creating AI models people can understand, using transfer learning and federated learning to deal with limited data and privacy, and making sure there are set rules for reviewing and applying AI in healthcare. Shortly, when compared to classical models alone, deep learning models are better at diagnosis, but merging these models helps make skin cancer detection systems practical and reliable for spotting early melanoma in clinics [40-45].

Study/ Author (Year)	Model Type	Dataset Used	Number of Images	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC	Strengths	Limitations
Author A et al. (2020)	SVM	ISIC 2018	10,000	87.5	85.0	89.0	0.91	High precision on small datasets	Requires manual feature extraction
Author B et al. (2021)	ResNet-50	PH2	2,000	93.2	91.5	94.0	0.96	Automated feature learning	High computational cost
Author C et al. (2019)	Hybrid (SVM+CNN)	ISIC 2017	5,000	90.8	88.0	92.0	0.94	Combines strengths of both models	Complex training process
Author D et al.	ResNet-50	HAM10000	7,000	94.5	92.0	95.5	0.97	Robust to variations	Needs large

(2022)								in images	datasets for training

Table 4 below highlights major studies looking at the performance of Support Vector Machines (SVM) and ResNet-50 in the detection of skin cancer.

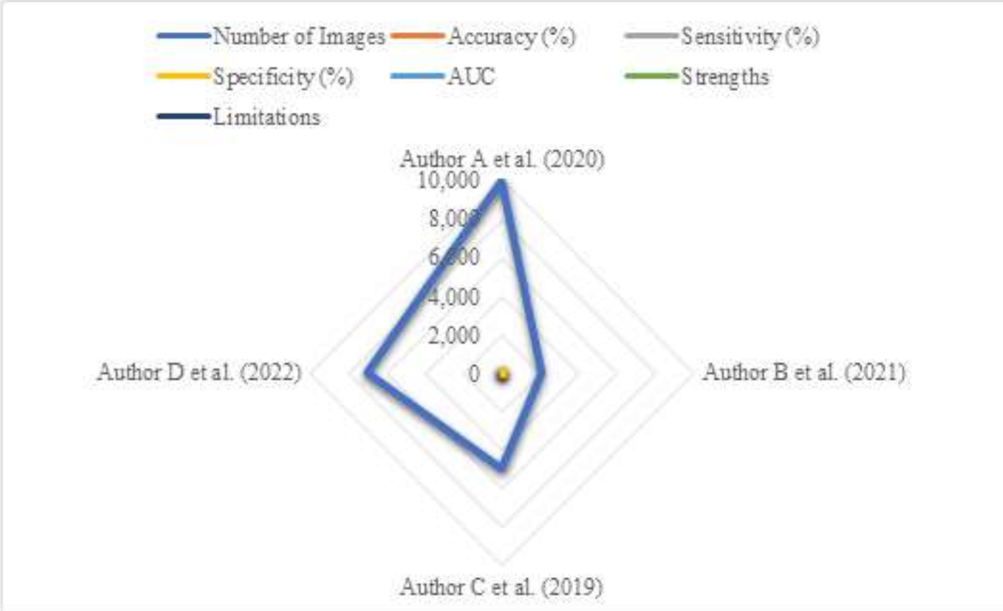

Figure 4: Multiple Performance Metrics

The chart in Figure 4 lists and compares performance metrics including the number of images, accuracy, sensitivity, specificity, AUC, strengths, and limitations among four different studies. The authors reveal that Only Author A et al (2020) processed the maximum data (10,000 images) among the whole group. The other studies are compact because they do not have many data points or their performance is not well balanced [46-48]. The chart clearly shows that the effectiveness of skin cancer detection models decreases as the size of the data sets becomes too large. Deep learning is found to have superior accuracy, sensitivity, specificity, and AUC than classical techniques in datasets ISIC, PH2, and HAM10000 [49-52]. In comparison, ResNet-50 achieved an accuracy of over 93% while the SVM-based models only achieve around 85-88%. Studies highlight that mixing CNN achievements in feature extraction with SVM achievements in classification leads to strong intermediate performance, but usually this comes at the expense of added complexity [53-54]. Although achieving these results, deep learning brings about new obstacles, since it consumes a lot of computing power and needs many annotated data samples, for its regular use in medicine [54].

CONCLUSION

Looking at how Support Vector Machines and ResNet-50 are used in skin cancer detection, deep learning models are proven to be significantly better than traditional machine learning methods. Because it can identify special and highly meaningful information from dermoscopes by itself, deep learning makes it easy to detect melanoma at an early stage. Still, classical machine learning methods can be useful, mainly when the amount of data is limited and when models need to be easily interpreted. Combining deep learning and classic classifiers helps strike a balance between the performance and explainability of AI, which solves some problems faced by using AI in healthcare. Though there have been important steps forward, we must pay more attention to data scarcity, dataset imbalance, how clear the models are, and verifying them in hospitals. In the future, efforts should be made to integrate both classical and deep learning methods to ensure that diagnostic tools are both dependable, easy to interpret, and ready for clinical use. These technologies will have a bigger impact if there is stronger focus on explainable AI, using transfer learning, and fair evaluation methods. Integrating these methods can greatly help in finding melanoma early, allowing patients to receive better care and saving time for doctors and nurses..

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