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Derma CNN - Convolutional Neural Network for Skin Cancer Lesion Classification

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Abstract

Skin cancer is among the most common and even fatal diseases in the world where early diagnosis and proper classification of skin lesions are significant toward increasing chances of survival of the patients. Recent progress in artificial intelligence, especially machine learning (ML) and deep learning (DL) has shown good outcomes in automated analysis of skin lesions through dermatoscopic images. This paper is a comparative analysis of the classical machine learning and deep learning models of the skin cancer lesion classification. Skin Cancer MNIST: HAM10000, a popular dataset, is utilized to compare the performance of Support Vector Machines (SVM), Random Forest (RF), XGBoost, Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN). It is followed by a systematic preprocessing and augmentation pipeline to improve image quality and reduce the issue of class imbalance. According to experimental findings, CNN has the highest classification accuracy of 96.54, which is better than conventional ML models. The comparative analysis discusses a trade-off between model predictive performance and model interpretability, which are insightful to guide clinical decision-support system development.

Keywords: Artificial Intelligence, Machine Learning, Deep Leaning, Classification, Convolution Neural Network, SVM

1. Introduction

Skin cancer has become one of the most popular subjects in the public health discussion because of its growing prevalence and the possible serious clinical effects in case of inadequate diagnosis and treatment in its early stages[1]. The disease includes various subtypes, such as melanoma, squamous cell carcinoma (SCC), basal cell carcinoma (BCC), and other rarer malignancies, each possessing distinctive visual features and risk profiles[2]. Of these, melanoma is the most aggressive of them all and causes a good percentage of deaths due to skin cancer, therefore, its early and accurate detection is very important[3].

Conventional methods of diagnosis such as visual inspection, dermoscopy, and histopathological are highly dependent on the interpretation of experts and are prone to inter- observer variability[4]. Despite the fact that dermoscopy enhances the level of diagnostic accuracy, its performance is

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influenced by the level of expertise and experience of a clinician. Consequently, computer-aided diagnosis (CAD) systems which are automated have become more and more popular as aides to dermatologists[5].

Over the recent years, machine learning and deep learning have demonstrated impressive performance in analytical processes in medical imagery and specifically in the field of dermatology[6][7]. Advanced neural networks, particularly convolutional neural networks can learn intricate spatial features without any pretraining (although frequently outperforming human performance in controlled environments. Nevertheless, set data imbalance, low interpretability, and computing problems are unresolved research problems.

1.1. Research Contribution

a. A combined comparative study of classical machine learning and deep learning models on a standard benchmark dataset.
b. A massive preprocessing and augmentation pipeline to enhance the quality of data and the robustness of the models.
c. A comprehensive performance assessment that identifies the strengths and weaknesses of each of the methods in a clinical setting.

Figure 1- Cancerous Patches

1.2. Paper Organization

The rest of this paper is structured in the following way. Section 2 contains the background of skin cancer diagnosis and automated lesion classification methods, and Section 2.1 mentions identified research gaps. The proposed methodology is specified in Section 3, with a focus on the data set to be used to perform the experiments in Section 3.1, the preprocessing and data augmentation methods in Section 3.2, and the classification models in Section 3.3. Section 4 shows the performance analysis and the experimental results. Section 5 is a comparative assessment with the existing studies. Section 6 identifies the main issues related to automated skin cancer lesion classification systems, and the future research directions are specified in the section 7. Lastly, the paper ends with Section 8, which offers a summary of the key findings and contributions of the current paper.

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2. Background

Cutaneous malignancies have seen an important shift in diagnosis of their pathways in the last several decades, where manual examination has been replaced by advanced artificial-intelligencecontained systems. Previously a significant part of the detection process relied on a visual examination with naked eyes; the human eye is subjective and often gives inconsistent results due to inter observer reliability.

In order to overcome these limitations, dermoscopy is a non-invasive imaging modality that has become very popular in order to help provide visualization of the underlying cutaneous structures after magnification. Being adequately trained, clinicians will be able to recognize morphological patterns in the superficial dermis that cannot be observed in the course of unaided inspection. Subsequently, there is a growing tendency of specialists to use dermoscopy in the diagnosis of melanoma, and its use has risen into primary care. Dermoscopy provides great improvement in the accuracy of diagnosis of a basal cell carcinoma (BCC), optimizes the process of triage, detects low-risk lesions in primary care, and provides a sense of security when benign lesions necessitate no further treatment [8].

In the past 20 years, the dermoscopy has shown a high level of efficiency in the diagnosis of melanoma as well as non-melanoma skin neoplasms such as basal cell carcinoma. In addition to melanocytic lesions, dermoscopy has been useful when it comes to identifying non-melanocytic tumors extending its clinical usefulness [9].However, the method is still overly dependent on clinician experience and subjective interpretation is still having a role in diagnostic consistency.

Conventional diagnosis is based on the histopathologic analysis that follows the biopsy, which is considered as the gold standard. However, inherent limitations are attached to this methodology. Histologic examination of the suspected non-melanoma skin cancer (NMSC) lesions is invasive, time-consuming, and is often vulnerable to inter-observer variance. Studies have shown that the histologic subtype of preoperative biopsy specimens of basal cell carcinoma is usually not the same as that in excision specimen and some discrepancies were reported as 10 per cent to 81 per cent. In addition, incisional biopsies can be insufficient in the true tumor subtype representation and concordance between Mohs surgeons and dermatopathologists has been variable [10].The problems highlighted it is critical to have more reliable, nondestructive diagnostic options.

Solving these issues, the modern research has switched to machine-learning and deep-learning systems of lesion-classification frameworks. The systems envision providing a way of supplementing clinical decision-making with fast, objective, and reproducible analysis of dermatoscopic images. New models of artificial-intelligence, which consider a variety of clinical dermatology activities and knowledge transfer across different fields, are particularly attractive to clinical application. Also, multimodal techniques, including the combination of ultrasound imaging with dermoscopy, are investigated to make the diagnostic further and more precise [11].

Convolutional neural networks (CNNs) are one of the recognized automated methods and continue to outperform in discriminative feature extraction of dermatoscopic imaging and outperform traditional machine-learning models regularly. However, more classic algorithms like supportvector machines (SVMs) and random forests are also still relevant due to their less demanding nature in computation and more comprehensible nature, which is also considered

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important in the clinical environment. In spite of the fact that several studies have articulated the concept of hybrid and ensemble paradigms to enhance the strength and generalization, most of the studies are not able to conduct extensive comparative analysis since they directly examine individual algorithms in isolation.

To fill this gap in the existing body of research, the current study realizes a systematic comparative evaluation of a collection of machine-learning and deep-learning models under the same experimental design. By carefully examining performance measures, advantages and drawbacks of each methodology, the current study aims at contributing to the evolution of reliably and effectively automated systems that can be suitably incorporated into clinical workflows without disrupting the accurate diagnostic analysis and clinical outcomes in cutaneous oncology.

2.1. Research Gaps

Although there are significant gains in automated skin-cancer diagnostics, most reports consider only classical methods of machine-learning or deep-learning systems separately. Heterogeneous datasets, inconsistent preprocessing, and different evaluation protocols are also used to compare studies in a comparative study and this conflicts with objective performance comparison. As a result, at this time, no single experimental system is available that comparatively assesses traditional machine-learning models and CNN-based deep-learning systems on the same conditions. This gap is important to a clear knowledge on the trade-offs between accuracy, computational complexity and clinical applicability in automated skin-cancer lesion classification. Based on these problems, the current work contains a comparative analysis of several ML and DL methods of classifying lesion types of skin cancer with the use of the HAM10000 dataset.

3. Methodology

3.1. Dataset Description

The current study uses the Skin Cancer MNIST: HAM10000 dataset; this data set is made up of 10,015 DSS images; these images were obtained by a heterogeneous group of populations and disease acquisition conditions. The data set will have seven different categories of cutaneous lesions, and these will consist of both benign and malignant entities. The canonic nature of imaging parameters and lesion phenotypes makes this corpus especially suitable to benchmark automated classification algorithms.

3.2. Preprocessing and Augmentation of Data

To achieve the homogeneity of the data set and also to strengthen the generalization ability of the predictive models, a sequence of preprocessing procedures was carried out. Image-enhancement processes like noise-reduction and contrast-normalization were used to make the recordings more aesthetically true-to-life. All the images were then resized to a pre-programmed resolution and then normalised to equalize the distribution of pixel intensities through the data set. To prevent the problem of class imbalance, a strategy used was a combination of oversampling and dataaugmentation strategies. Augmentation schemes expanding in rotation, horizontal, and vertical flipping, as well as, scaling, were implemented in order to enhance data diversity and to decrease

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the tendency towards over-fitting. Subsequently, the augmented data set was divided into separate training and validation subsets to be used in the further assessment of the model.

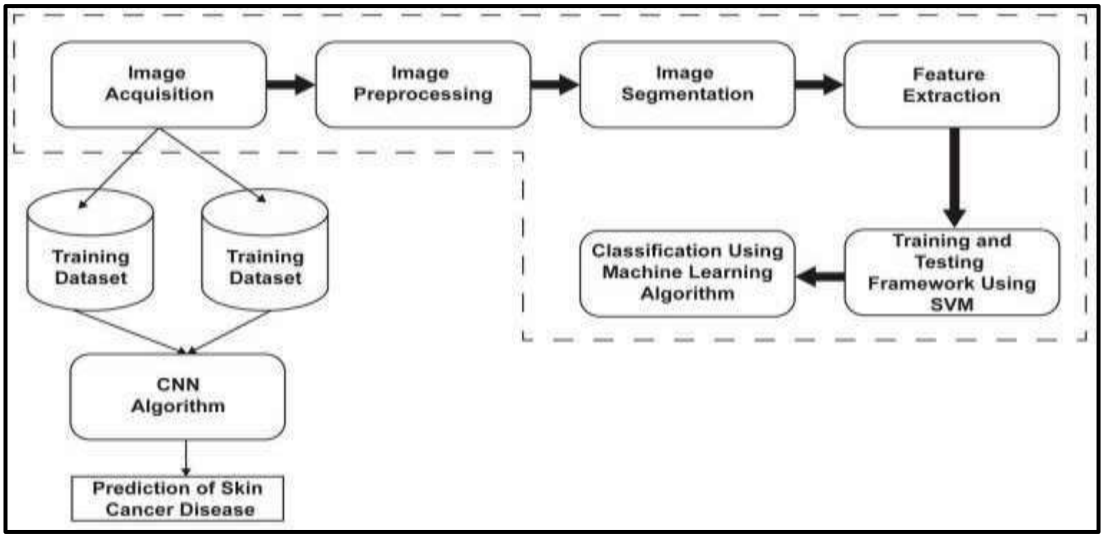

Figure 2 Work Flow Diagram

3.3. Classification Models

The following instantiations and evaluations were done on a variety of machine-learning and deep-learning frameworks:

i. **Support Vector Machine (SVM)-** SVM method is created to determine the best decisionline by maximising the difference between dissimilar groups. It is applicable to high dimensional feature space, though it is computationally intensive when dealing with large corpora. They are called support vectors because they play a special role as reference points[12][13]. SVMs may struggle with large datasets or datasets with high dimensionality, as they require significant computational resources for training. Additionally, SVMs may not perform as well on non-linear data or in scenarios with imbalanced classes.

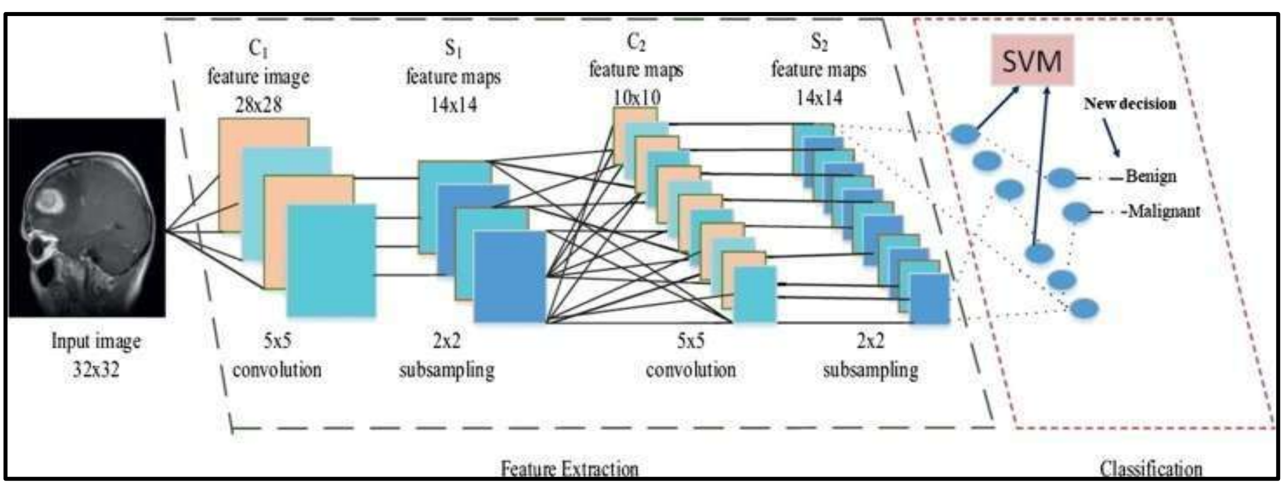

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Figure 3 Architecture of SVM

ii. **Random Forest (RF)-** Here, the ensemble approach combines a number of decision trees in order to increase the robustness of classification, as well as to reduce over-fitting. Random Forest models are also relatively easy to interpret compared to more complex models like neural networks[14][15]. While Random Forest models generally perform well on a wide range of datasets, they may not always achieve the highest accuracy compared to more advanced techniques like deep learning. Additionally, Random Forest models may require careful tuning of hyperparameters to optimize performance.

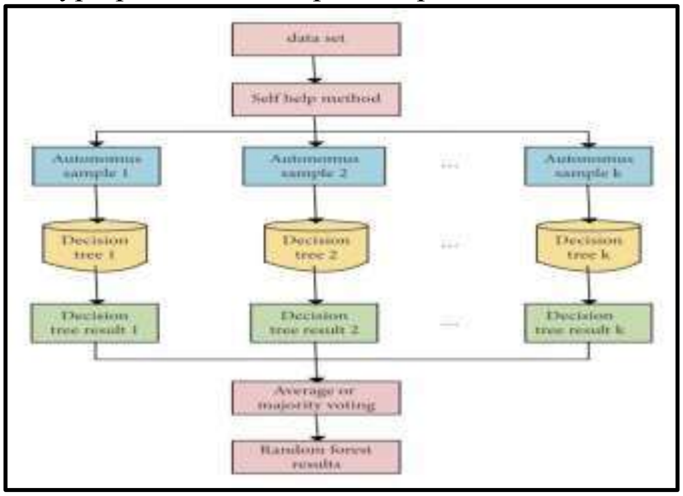

Figure 4 Architecture of Random Forest [16]

iii. **XGBoost-** XGBoost is a gradient-boosting library that boasts of its performances in terms of its computational efficiency and high predictive accuracy on structured data. XGBoost models are also relatively interpretable, making them suitable for applications where model transparency is important[17]. XGBoost may not perform as well on highdimensional data or data with complex relationships. Additionally, hyperparameter tuning

may be required to optimize performance, which can be time-consuming and computationally intensive.

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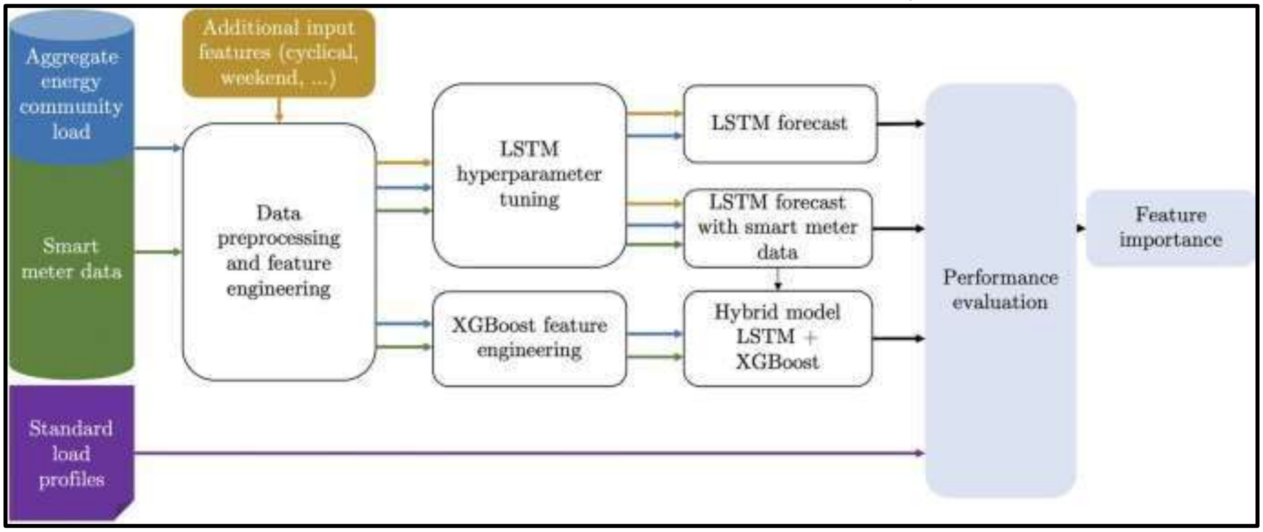

Figure 5 XGBoost Architecture

iv. **Recurrent Neural Network (RNN)-** The usefulness of RNNs in sequential dependencies was explored; nevertheless, the application of this information in the relation to image classification of stationary images is exploratory[18]. They can capture long-term dependencies in sequential data, making them potentially useful for analyzing sequences of skin lesion images over time[19]. RNNs may suffer from vanishing gradient problems during training, limiting their ability to capture long-range dependencies effectively. Additionally, RNNs may require substantial amounts of training data to generalize well to unseen sequences.

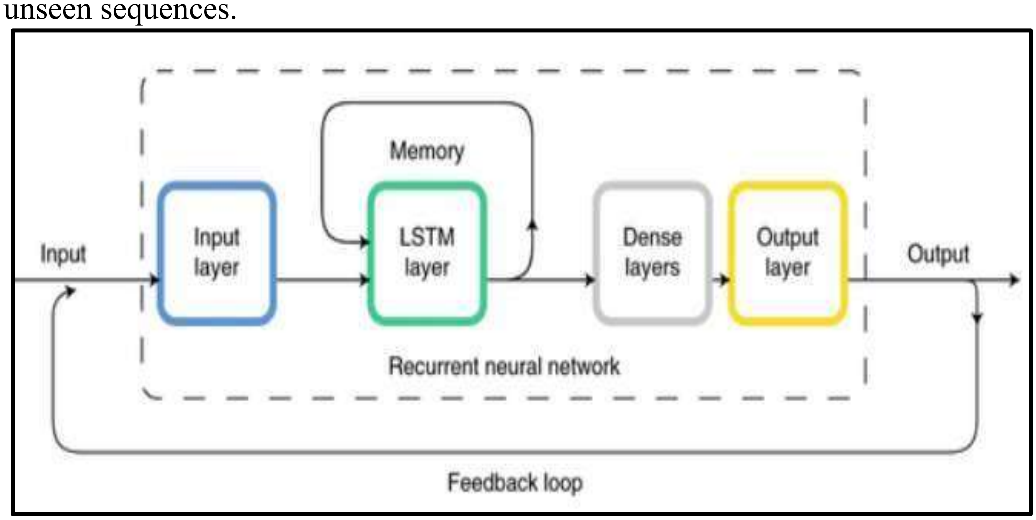

Figure 6 XGBoost Architecture

v. **Convolutional Neural Network (CNN)-** CNNs automatically acquire hierarchical spatial representations of image and form the state-of-the-art methodology of visual recognition tasks. They can discover important features from raw pixels, so engineers do not have to create these manually[20][21]. CNNs are computationally intensive and require large

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amounts of annotated data for training. Additionally, interpreting the decisions made by CNN models can be challenging, limiting their applicability in settings where interpretability is crucial.

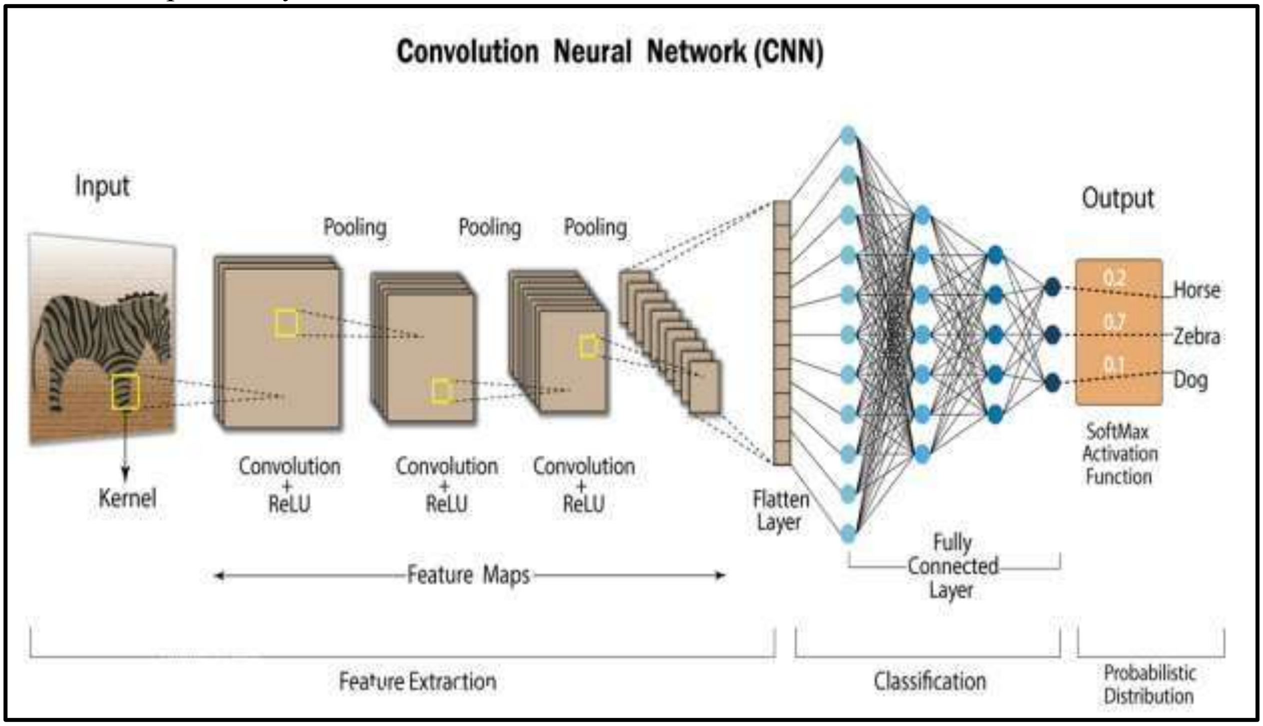

Figure 7 Architecture of CNN

4. Result

The Skin Cancer Lesion Classification model employed various machine learning algorithms to accurately classify skin lesions, aiming to improve diagnostic capabilities in the fight against skin cancer. Here are the accuracy scores obtained for each model:

Table 1 Accuracy Chart

Algorithm	**Accuracy**
Support Vector Machines (SVM)	88.30%
Random Forest	86.64%
XGBoost (XGB_model)	93.55%
Recurrent Neural Network (RNN)	92.00%
Convolution Neural Network (CNN)	96.54%

These results indicate the performance of each model in classifying skin cancer lesions based on the features extracted from dermatoscopic images. The CNN model achieved the highest accuracy at 96.54%, demonstrating its effectiveness in accurately identifying different types of skin lesion.

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The experimental findings indicate that CNN-based deep-learning networks always have a high accuracy in classification compared to conventional machine-learning methods. This benefit is attributed to the fact that CNNs are able to automatically extract hierarchical and discriminative features directly on dermoscopic images. However, in some cases, classical machine-learning models still hold up, especially where computational efficiency and interpretability of the model are of importance. These points highlight the trade-off that must be made when choosing the model to be applied to real-world clinical settings.

Discussion

The experimental results reveal notable performance variations across different models. Deep learning approaches, particularly CNNs, significantly outperform classical machine learning methods due to their ability to automatically learn discriminative features. However, traditional models such as SVM and Random Forest offer greater interpretability, which is often preferred in clinical settings.

Data quality and diversity play a critical role in determining model performance. The HAM10000 dataset's comprehensive design contributes to improved generalization, although further expansion across demographic groups could enhance robustness. While laboratory-level results are promising, real-world clinical deployment introduces challenges related to system integration, regulatory approval, and user trust.

5. Comparison

A detailed comparison with existing studies is provided in Table 2. The survey demonstrates that recent CNN-based approaches consistently achieve high accuracy across different datasets. The results of the present study are competitive with state-of-the-art methods, reinforcing the effectiveness of deep learning for automated skin cancer diagnosis.

Table 2 Survey Table

Ref	Year	Objective	Model	Dataset	Accuracy
[22]	2020	Using CNN to spot and tell apart skin cancer from skin rash in pictures	CNN	A/N	80.2%
[23]	2020	Identifying the kinds of skin lesion classes, including malignant skin cancer and melanoma	5-layer CNN	PHP	95%
[24]	2020	Using a two-stage network to find melanoma and nonmelanoma images.	Deep Residual Network (DRN)	ISIC	88.7%

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[25]	2020	The use of a hybrid method that takes advantage of the main strengths of one approach to find melanoma.	CNN, KNN, and SVM	ISIC	88.4%
[26]	2021	To use machine learning and image processing to determine if a skin lesion is benign or malignant	Random Forest classifier	ISIC-ISBI 2016	93.89%
[27]	2022	investigation to assess EfficientNets B0-B7's performance on the skin cancer classification task and the HAM10000 dataset	EfficientNet B4	HAM10000	87.91%
[28]	2023	To create a DCNN-based model that can accurately and automatically distinguish between melanoma and non-melanoma kinds of skin cancer.	EfficientNet architecture , transfer learning techniques	ISIC-2019 and ISIC - 2020	96%
	2024	**Proposed Work**	CNN	HAM10000	96.54%

6. Challenges

i. **Model Performance Discrepancies:** The observed variations in accuracy among different models highlight the importance of algorithm selection and feature representation in skin lesion classification. While the CNN model demonstrated the highest accuracy at 96.54%, other models such as Random Forest and XGBoost also performed reasonably well. Understanding the underlying factors contributing to these performance differences can inform the refinement of existing models and the development of novel approaches. ii. **Complexity versus Interpretability:** A notable consideration in model selection is the trade-off between complexity and interpretability. Deep learning models, for example CNNs, tend to work very accurately, but their reasoning is quite difficult to understand. At the same time, traditional machine learning algorithms such as Random Forest and SVMs give easier-to-understand explanations but could result in slightly lower accuracy. Having a model that is the right balance between being complex and easy to understand is necessary for it to be helpful in the clinic.

iii. **Data Quality and Diversity:** The way machine learning models assess situations is mainly influenced by the quality and variety of the training data they are given[29]. The "Skin

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Cancer MNIST: HAM10000" dataset was specially made to fix problems of both size and diversity. It is also important to increase the size and variety of datasets so they include numerous skin types, diverse lesions and different demographic groups. Increasing the quality and variety of data in the dataset helps models perform well and stay robust in many types of clinical use.

iv. **Clinical Implementation Challenges:** Although our experiments obtain good results in the laboratory, bringing these results to practical health care is difficult. Medical staff and regulators need to accept automated lesion classification tools and they should fit well with current healthcare systems for their proper use in real-world settings. To get through these obstacles, researchers, clinicians, policymakers and industry players must work closely together.

7. Future Directions

From this investigation, numerous paths for further development and research become open. Examples are using many models together, working on transfer learning to use prior models and big data and linking data such as records and genetic backgrounds to help in distinguishing the lesion.Additionally, conducting prospective clinical studies to evaluate the real-world performance and impact of automated lesion classification systems on patient outcomes is paramount.

8. Conclusion

This paper presents a comprehensive comparative analysis to machine learning and deep learning approaches to classify lesions of skin-cancer in the HAM10000 dataset. Experimental evidence shows that convolutional neural networks outdo other techniques, however, standard machinelearning models still make sense based on their higher interpretability and less computational cost. Future research directions will be to include explainable artificial-intelligence methods, multimodal data fusion, and future clinical validation, which will encourage translation to clinical practice. The framework that is suggested increases the incremental growth of sophisticated dermatological diagnostics systems.

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