DigiScope: IoT-enhanced deep learning for skin cancer prognosis

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ABSTRACT

In dermatology, early identification and intervention are crucial for optimizing patient outcomes in skin cancer care. Recent technological advances, particularly in the internet of things (IoT), have led to significant growth in telemedicine. This study introduces a cutting-edge system that proactively predicts the emergence of skin cancer by combining deep learning algorithms, IoT devices, and sophisticated medical imaging techniques. The experimental setup leverages a high-resolution mobile camera for dermoscopy, associated with a cloud-integrated machine learning framework. The proposed algorithm comprehensively examines lesion characteristics, Utilizing color, texture, and shape characteristics to evaluate the probability of malignancy. Subsequently, a cloud-hosted machine learning model analyzes and scrutinizes the collected data, yielding a thorough diagnostic evaluation. Initial results reveal that this system achieves an impressive predictive accuracy rate exceeding 97.6%, enabling swift and efficient skin cancer detection. These promising findings emphasize the potential for rapid, efficient, and proactive diagnosis, significantly improving patient prognosis and reinforcing the value of telemedicine in contemporary healthcare.

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1. INTRODUCTION

Skin cancer poses a significant health challenge across the globe, emphasizing the need for effective detection and treatment methods to improve patient outcomes and reduce its impact. The rise of technology in healthcare offers new possibilities for tackling this challenge, as artificial intelligence (AI) and the internet of things (IoT) are becoming powerful tools in the fight against skin cancer. Ben-Bouazza *et al.* [1] by leveraging these technologies, we are entering an era where early detection and precise diagnosis are increasingly within reach. Azeroual *et al.* [2] AI algorithms are capable of analyzing enormous volumes of data, unveiling intricate patterns often missed by human clinicians. This capability is further enhanced by the integration of data streams from wearable sensors and medical imaging devices within the IoT framework, enabling comprehensive analyses. Recent studies underscore the transformative power of these technologies, Hoang *et al.* [3] with deep learning algorithms redefining lesion detection and classification. IoT-enabled devices, such as intelligent skin patches, facilitate advanced data acquisition and transmission for in-depth analysis, thereby pushing the boundaries of medical innovation.

Gajera *et al.* [4] employed deep features derived from pre-trained convolutional neural network (CNN) models to assess dermoscopic images for melanoma diagnosis, advocating for border localization to safeguard critical skin lesion sites. A total of eight CNN models were systematically examined for the purpose of feature extraction, utilizing four distinct datasets in the experimental procedures. The integration of DenseNet-121 with a multilayer perceptron yielded a commendable classification rate. Kumar *et al.* [5] effectively discerned preliminary indicators of three distinct types of skin cancer through the application of computational methodologies. They employed a deep evolutionary artificial neural network (DEANN) for the classification of skin cancer, alongside techniques such as local binary patterns (LBP), gray level co-occurrence matrix (GLCM), color space analysis, and RGB techniques to extract pertinent image features critical for the accurate classification of the condition. Chaturvedi *et al.* [6] proposed a methodology for the classification of Malignant Cutaneous Melanoma that demonstrates superior performance compared to both dermatological assessments and existing deep learning approaches. Khan *et al.* [7] developed a system that integrates deep learning models, specifically leveraging DenseNet for classification purposes and mask regional convolutional neural network (Mask-RCNN) for segmentation tasks. Srinivasu *et al.* [8] utilized MobileNet V2 as the selected architecture for the classification of diverse dermatological conditions, integrating long short-term memory (LSTM) to enhance the model's performance. Hosny *et al.* [9] presented a novel methodology for the classification of skin lesions, utilizing transfer learning in conjunction with a deep neural network architecture known as AlexNet. The public database ISIC 2018 served as the foundational dataset for the training, testing, and comparative analysis of the proposed methodology against state-of-the-art techniques. The methodology effectively classifies seven unique categories of skin lesions, with the authors reporting outstanding outcomes in classification performance. Sae-Lim *et al.* [10] employed a modified MobileNet architecture for the classification of skin lesions. The findings indicated that the modified model exhibited superior performance compared to the conventional MobileNet model, as evidenced by enhancements in accuracy, specificity, sensitivity, and F1-score. During the preprocessing phase, the implementation of data upsampling and data augmentation techniques proved beneficial in addressing class imbalance. Furthermore, data augmentation served as a mechanism to mitigate the risk of overfitting within the model. Zaqout *et al.* [11] have formulated an automated diagnostic framework aimed at the preliminary evaluation of melanoma, utilizing image processing techniques that are grounded in the widely recognized ABCD medical protocol. The proposed system employs a range of image processing techniques to facilitate precise, rapid, cost-effective, and readily accessible diagnosis of melanoma. Hasan *et al.* [12] introduced an innovative automatic skin lesion segmentation network designated as DSNet. This network exhibits robustness and incorporates a proposed loss function that integrates a binary cross-entropy component alongside an intersection over union component. Adegun and Viriri [13] developed a deep learning-based computer-aided diagnosis system aimed at the detection and identification of skin lesions for the purpose of diagnosing skin cancer. Chatterjee *et al.* [6] introduced an innovative kernel sparse coding methodology aimed at the segmentation and classification of skin lesions. Their approach demonstrated competitive performance relative to alternative techniques in experimental evaluations utilizing both dermoscopy and digital datasets. Sàez et al. employed a computerized system designed to quantify melanoma thickness through the analysis of dermoscopic images. Yu *et al.* [14], Hameed *et al.* [15], Khan *et al.* [16], Hoang *et al.* [3], Zhang *et al.* [17], Periera *et al.* [18], Shetty *et al.* [19], Dhivyaa *et al.* [20], Mahbod *et al.* [21], and Alenezi *et al.* [22] have made significant contributions to the domain of skin lesion classification. Yu *et al.* [14] introduced an innovative methodology for the classification of dermoscopy images, employing a compact architectural framework alongside local descriptor encoding techniques. The convolutional features were extracted from an image employing a deep residual network, followed by the application of the fisher vector technique to encode these features into more intricate representations. Hameed *et al.* [15] employed a combination of traditional machine learning methodologies alongside advanced deep learning approaches to assess early-stage skin lesions. The deep learning methodology utilized transfer learning directly from the images, whereas the conventional approach initially conducted pre-processing, categorization, feature extraction, and subsequent categorization processes. The proposed methodology demonstrated superior performance compared to the multi-class single-level classification algorithm, attaining elevated accuracy across both approaches. Khan *et al.* [7] introduced an innovative computer-aided diagnosis (CAD) system aimed at the classification of skin lesions through the application of deep learning methodologies. The system employs ResNet-50 and ResNet-101 architectures for the extraction of features from enhanced dermoscopic images, utilizing a novel methodology referred to as KcPCA for the selection of significant features. A multi-class support vector machine (SVM) utilizing a radial basis function kernel is employed, incorporating the upper 60% of these features as input. Hoang *et al.* [3] developed a straightforward methodology for the classification of skin lesions, demonstrating superior performance compared to 20 alternative methods while necessitating 79 times fewer parameters. The researchers employed a deep learning methodology to effectively segment and classify skin lesions, attaining remarkable outcomes when the lesion's foreground is discernible from the background through texture and color differentiation. Zhang *et al.* [17] proposed an innovative methodology utilizing a CNN framework for the diagnosis of skin cancer. A modified variant of the whale optimization algorithm was employed to enhance the efficacy of CNNs and to minimize the discrepancy between the network's output and the intended output. Thurnhofer-Hemsi et al. presented an innovative methodology for the classification of skin lesions through the application of deep CNNs, demonstrating enhanced reliability compared to traditional CNN classification methods. Shetty *et al.* [19] proposed a methodology for the classification of skin lesion photographs employing CNN and machine learning techniques, with outcomes assessed utilizing the HAM10000 dataset. Dhivyaa *et al.* [20] integrated learning theory with the decision tree-based random forest classification methodology to enhance the accuracy and robustness of skin lesion image categorization. Mahbod *et al.* [21] conducted an investigation into the influence of image dimensions on the efficacy of transfer learning classification in the context of skin lesion analysis. Alenezi *et al.* [22] introduced an innovative approach for the classification of skin lesions, which integrates wavelet-based preprocessing techniques, deep residual neural networks, and extreme learning machine classifiers.

However, despite these advancements in skin cancer detection and diagnosis, individuals in rural areas continue to face significant barriers to timely and accurate healthcare access. Current technologies, including telemedicine and existing mobile health solutions, often fall short in providing the necessary high-resolution imaging and robust computational resources needed for precise skin cancer classification. Ben-Bouazza *et al.* [23] there is a noticeable lack of integration between mobile imaging devices and cloud-based deep learning models that can bridge the diagnostic gap between urban and rural populations. This gap underscores the need for an architecture that not only facilitates high-quality dermoscopic imaging but also ensures seamless data transfer and analysis in cloud environments. Furthermore, there is a critical need for a system that delivers diagnostic insights to remote healthcare providers, ensuring that patients in underserved areas receive comparable levels of care to those in urban centers [4]. In light of these shortcomings, this paper proposes a new architecture aimed at improving skin cancer classification, specifically focusing on individuals in rural areas who may have limited access to healthcare. The architecture combines a high-resolution mobile camera designed for dermoscopy with a deep learning model hosted on the cloud. Ben-Bouazza *et al.* [1] this setup enables not only the capture and analysis of dermoscopic images but also the seamless transfer of data to cloud servers equipped with ample computational resources for thorough analysis. The resulting insights are then shared with medical centers, allowing healthcare professionals to remotely access diagnostic results. This method ensures that patients in rural areas receive the same level of diagnostic scrutiny as those in urban settings, thereby closing a significant gap in healthcare accessibility [12].

This research has the potential to significantly improve early diagnosis and timely intervention for skin cancer, particularly in underserved rural communities where access to specialized healthcare is limited. The proposed deep learning model is instrumental in facilitating a thorough examination of skin lesions with enhanced precision and efficiency, far surpassing traditional approaches that often rely on manual analysis [24]. By enabling timely detection and efficient diagnostic processes, the system ensures that treatment can commence promptly, leading to better patient outcomes and potentially reducing mortality rates associated with skin cancer. Beyond its academic contributions, this research offers practical applications in real-world scenarios, such as mobile clinics and telehealth platforms, leading to positive impacts on global health outcomes and equity in healthcare access [25]. The remainder of this paper is organized as follows. In section 2, the methods and Materials section provides a detailed account of the techniques and technologies used in the study, including the unique architecture proposed for classifying skin cancer. This section also covers the workflow of Digiscope in Node-Red, demonstrating how data is processed and analyzed in a real-time environment. The Data section within this part gives a comprehensive overview of the types and sources of data utilized, with a specific emphasis on dermoscopic images obtained from rural areas. Section 3 presents the results and discussion, evaluating the effectiveness of the proposed methods. Section 4 discusses the challenges and limitations encountered during the study. Finally, section 5 provides the conclusion, encapsulates the principal discoveries and proposes possible directions for subsequent investigations.

2. MATERIALS AND METHODS
2.1. Dataset : HAM10000
2.1.1. Data settings

The HAM10000 dataset comprises a total of 10015 dermatoscopic images, which were meticulously gathered over a span of two decades from distinct locations. Specifically, these images were procured from two prominent sites: the esteemed Department of Dermatology at the Medical University of Vienna, Austria, and the reputable skin cancer practice of Cliff Rosendahl situated in Queensland, Australia. Gajera *et al.* [4] the Australian platform effectively employed PowerPoint files and Excel databases for the purpose of storing both images and meta-data. The Austrian site commenced the process of amassing visual representations prior to the advent of digital cameras, and subsequently preserved said images alongside corresponding metadata in diverse formats across varying temporal epochs. The lesion is positioned at the centre of the image, precisely at coordinates 800x600 pixels, with a resolution of 72 dots per inch (DPI).

The entirety of the data records pertaining to the HAM10000 dataset has been archived within the Harvard Dataverse repository. Table 1 presents a comprehensive summary of the image count within the HAM10000 training set, categorized by diagnosis, and juxtaposed with data from existing databases. The images and associated metadata can be accessed via the public ISIC archive, both through the archive gallery and through standardized API calls (https://isic-archive.com/api/v1).

Table 1. Summary of dermatological datasets: total images, pathologic verification percentages, and class distribution

Dataset	Total images	Pathologic verification	akiec	bcc	bkl	df	mel	nv	vast
PH2	200	20.5%	-	-	-	-	40	160	-
Atlas	1024	unknown	5	42	70	20	275	582	30
ISIC 2017	13786	26.3%	2	33	575	7	1019	11861	15
Rosenthal	2259	100%	295	296	490	30	342	803	3
ViDIR Legacy	439	100%	0	5	10	4	67	350	3
ViDIR MoleMax	3954	1.2%	0	2	124	30	24	3720	54
HAM10000	10015	53.3%	327	514	1099	115	1113	6705	142

The HAM10000 dataset, comprising 10,015 images of various skin lesions categorized into seven different classes [26]. The classes are visually depicted in Figure 1.

Figure 1. HAM10000 database classes

2.1.2. Data preparation

Applying a range of transformations to existing images is a common practice in skin cancer imaging to expand and diversify the dataset. Various techniques are employed to create different variations of images, including rotation, flipping, scaling, cropping, and color adjustment like shown in Figure 2, this process enhances the reliability and precision of machine learning models by enabling them to learn from a wider variety of data, minimizing overfitting and improving their capacity to generalize to unfamiliar images. Data augmentation plays a vital role in tackling the limited availability of labeled medical images and enhancing the effectiveness of skin cancer detection algorithms.

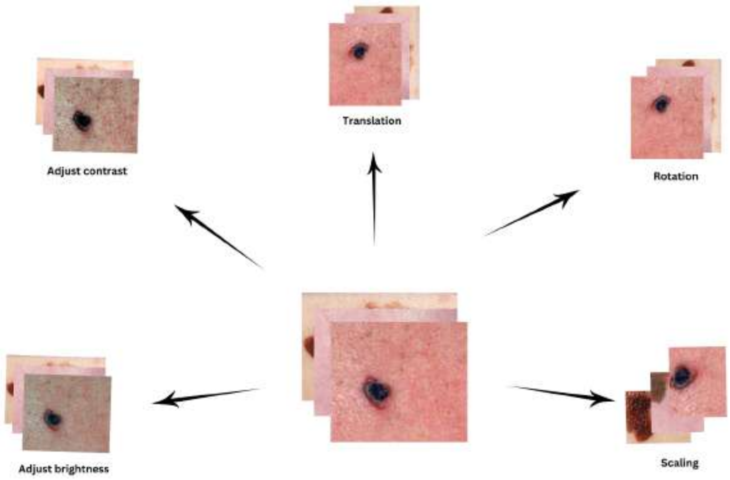

Figure 2. Data augmentation example

2.2. Workflow of the proposed approach

This flowchart in Figure 3 illustrates the workflow for a deep learning project focused on skin cancer classification using the HAM10000 dataset.

- HAM-10000: HAM10000 is a dataset containing images of skin lesions, used for training and testing the model.
- Pre-processing: the raw data from HAM10000 is pre-processed. Pre-processing might include tasks such as normalization, resizing images, data augmentation, and other techniques to prepare the data for training the model.
- Training model: after pre-processing, the data is fed into a machine learning model for training. This involves using algorithms to learn patterns from the training data.
- Classification: the trained model is then used for classification. This is where the model makes predictions on new, unseen data.
  - Yes (Successful classification): if the classification results are satisfactory, the workflow proceeds to deployment.
  - No (Unsuccessful classification): if the classification results are not satisfactory, the workflow moves to the results analysis phase.
- Results analysis: here, the results of the classification are analyzed. This step involves assessing the performance of the model, identifying any shortcomings, and understanding the reasons behind incorrect classifications.
- Hyperparameters update: based on the analysis, the model's hyperparameters are updated. Hyperparameter tuning is crucial for improving model performance. Once updated, the model is retrained with the new settings.
- Deployment: if the classification is successful, the model is deployed. Deployment means integrating the model into a production environment where it can be used for real-time predictions.
- Optimization: after deployment, the model is further optimized to enhance its performance and efficiency in the production environment.
- Real-world integration: the final step involves integrating the optimized model into real-world applications, making it accessible for end-users and ensuring it performs well in practical scenarios.predictions.

This workflow is iterative, with the loop between results analysis, hyperparameters update, and model training ensuring continuous improvement until satisfactory classification performance is achieved.

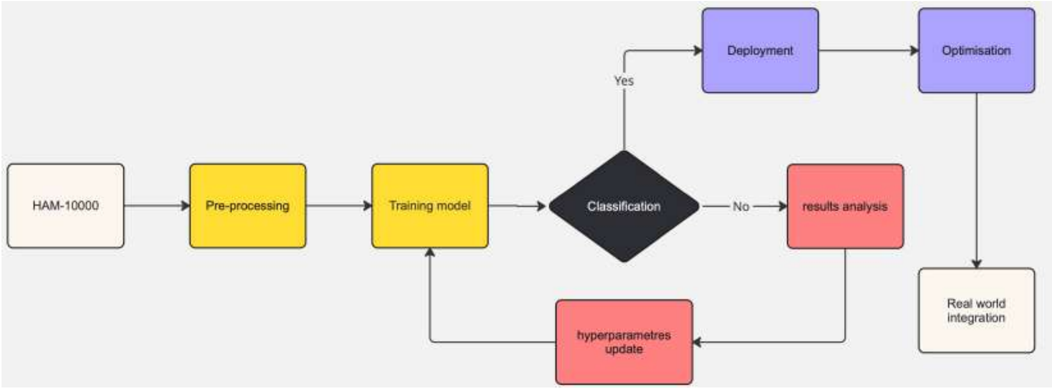

Figure 3. Workflow of the proposed approach

2.3. Workflow of the proposed architecture

In this scientific paper, we devised an entirely autonomous methodology that harnesses the power of CNNs to discern and classify cutaneous anomalies with utmost precision. The central emphasis of our study revolved around the exploration and evaluation of efficacious pre-processing methodologies and classification algorithms. In order to assess the efficacy of our methodology, we utilised the HAM10000 dataset, which encompasses a total of 10,015 diverse images depicting a wide range of skin lesions that have been meticulously classified into seven distinct categories. The sequential procedure that we employed is graphically represented in Figure 4. In the subsequent section, we shall embark upon an in-depth exploration of the data employed in this study, elucidating the preprocessing procedures that were implemented. Furthermore, we shall delve into the proposed theoretical framework, meticulously examining its intricate components and scrutinising its hyperparameters.

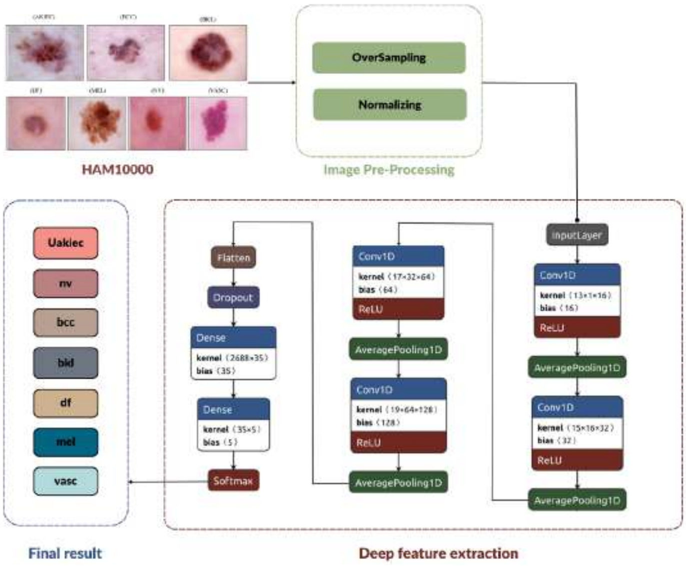

Figure 4. Workflow of the proposed architecture

2.3.1. The proposed architecture

In contrast to a traditional neural network, a CNN is designed to elucidate intricate patterns through the direct application of filters to the unprocessed pixels of an image. We used the Python libraries Tensorflow and Keras for our project to develop and implement the CNN model. Table 2 provides an overview of the layers and hyperparameters utilized in our network. These layers and hyperparameters play a crucial role in defining the structure and behavior of the CNN model.

Table 2. CNN layers and hyperparameters

Layer	Hyperparameters
Conv2D	16 filtres, 3x3 filter size, ReLu activation, same padding
Conv2D	32 filtres, 3x3 filter size, ReLu activation,
MaxPool2D	2x2 pool size
Conv2D	32 filtres, 3x3 filter size, ReLu activation, same padding
Conv2D	64 filtres, 3x3 filter size, ReLu activation, same padding
MaxPool2D	2x2 pool size, same padding
Flatten	2304 units
Dense	64 units, ReLu activation
Dense	32 units, ReLu activation
Dense	7 units, SoftMax activation

2.3.2. Model hyperparameters

We carefully selected specific commonly used hyperparameter values to ensure a more accurate evaluation of our model. Table 3 highlights the specific hyperparameter values employed in our CNN model. The following section explains the rationale behind selecting these values in our approach. By choosing appropriate hyperparameter values, we aimed to optimize the performance and effectiveness of our CNN model for skin lesion identification and classification:

- Optimizer: Adam was selected as the optimization technique for training deep neural networks due to its facile to use nature, computational efficiency, and efficacy in managing substantial volumes of data and parameters.
- Loss function: the loss function employed in the multi-class scenario is derived from the "sparse categorical cross-entropy" methodology, which facilitates the computation of the loss value.
- Epochs: the epoch count is set at 50. This was determined through experimentation, which found that 50 epochs resulted in a model with low loss and no overfitting to the training set (or the least amount of overfitting possible).
- Batch size: a series of preliminary experiments were conducted utilizing batch sizes of 20, 30, 60, and 90, with the findings indicating that a batch size of 128 yielded the most favorable outcomes.

Table 3. CNN model's hyperparameters

Hyperparametres	Value
Optimizer	Adam
Loss function	Sparse categorical cross-entropy
Epochs	50
Batch size	128

2.4. DigiScope framework

2.4.1. The proposed edge-AI framework

the Digiscope edge-AI framework is a novel medical AI paradigm that uses self-learning and large-scale data evolution. So in this Figure 5 we illustrates a system for managing skin disease data using IoT and cloud technologies, divided into three main parts:

- Edge devices: the edge devices section includes various devices such as dermatoscopic cameras, smartphones, smartwatches, and other IoT devices. These devices are responsible for collecting data related to skin diseases, including images and other health metrics. Once collected, the data is transmitted to the cloud using secure communication protocols facilitated by routers, ensuring that the data is sent efficiently and securely.
- Cloud: the cloud section represents the cloud infrastructure, which includes storage, processing units, and machine learning models. When data from the edge devices reaches the cloud, it is stored and processed.

The cloud infrastructure uses machine learning algorithms to analyze the data, providing insights and updates. The cloud also updates the model parameters based on new data, ensuring that the analysis remains accurate and up-to-date. The results of the data processing are then sent back to the edge devices and forwarded to the online medical services.

– Online medical services: the online medical services section includes various healthcare services such as telemedicine platforms, hospitals, ambulances, and healthcare providers. These services utilize the processed data and insights provided by the cloud to offer medical advice, diagnosis, and treatment options. By integrating the data from the cloud, healthcare professionals can access real-time updates and therapeutic protocols, which helps in improving patient care and outcomes. This part of the system ensures that the processed data is effectively used to provide timely and accurate medical services to patients.

This integrated system allows for efficient data collection, processing, and utilization, thereby enhancing the management and treatment of skin diseases through a connected and intelligent infrastructure.

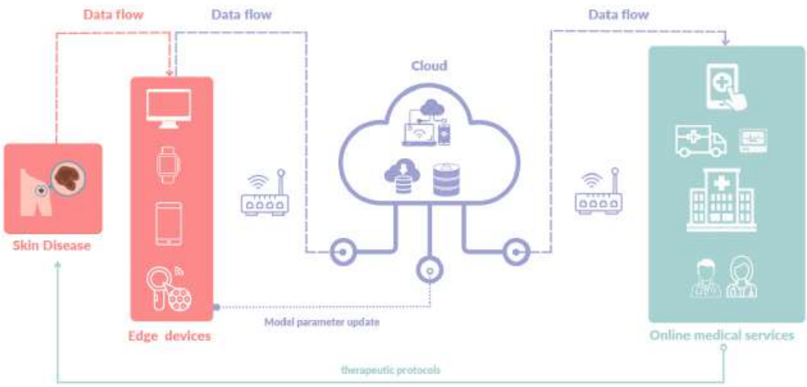

Figure 5. Digiscope: medical edge-AI framework

2.4.2. Digiscope workflow in node-RED

This Figure 6 illustrates the theoretical transfer of skin cancer picture data via a secure communication technique from a dermatoscopic camera to the cloud for processing. It illustrates projected data travel. The images are transmitted from edge devices to Google Cloud via MQTT, ensuring secure and efficient data transfer. The MQTT broker publishes the data to a pub/sub system, which forwards it to a vision module for processing. The processed data is then sent to an AutoML module for machine learning analysis. The analysis results update the IoT configuration and send commands back through the pub/sub system to the MQTT broker for terminal visualization. This simulation helps conceptualize the architecture, with real data flow planned for future projects.

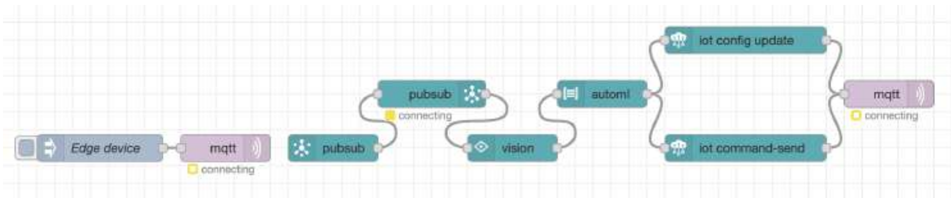

Figure 6. Digiscope workflow in node-RED

3. RESULTS AND DISCUSSIONS

In the present study, we implemented a CNN algorithm on a computational platform with a 16-gigabyte (GB) random access memory (RAM) and an Intel i7-8650U processor. This setup facilitated efficient data processing and execution of the CNN algorithm, with training averaging 25 minutes and classification of a single sample taking approximately 0.130 milliseconds. Python was utilized for implementation, employing libraries such as Keras, Pandas, and Scikit-Learn. The model demonstrated remarkable efficacy, achieving an overall precision rate of 98% on an independent test dataset and a loss rate of 19% during 50 epochs of training, with minimal signs of overfitting. Notably, data augmentation techniques enhanced model accuracy. The findings underscore the efficacy of deep learning models in the precise classification of skin lesions within practical, real-world contexts.

This research presents a comparative examination of our deep learning model in relation to established methodologies for the classification of skin lesions. revealing superior accuracy and speed compared to conventional techniques. The CNN algorithm's performance, as assessed by metrics such as recall, precision, F1-score, and support, wich can be calculated by the values shown in Figure 7, demonstrated comparable results to the SVM algorithm. However, our approach excels in efficiently identifying positive instances and minimizing false positives, as shown in Tables 4-6. The findings align with previous studies that emphasize the benefits of deep learning for skin lesion classification. Despite its strengths, our study has limitations, such as potential biases in the training data and the need for further validation in diverse clinical settings. Unexpectedly, the CNN model exhibited a notably low loss rate with data augmentation, underscoring its robustness in various conditions.

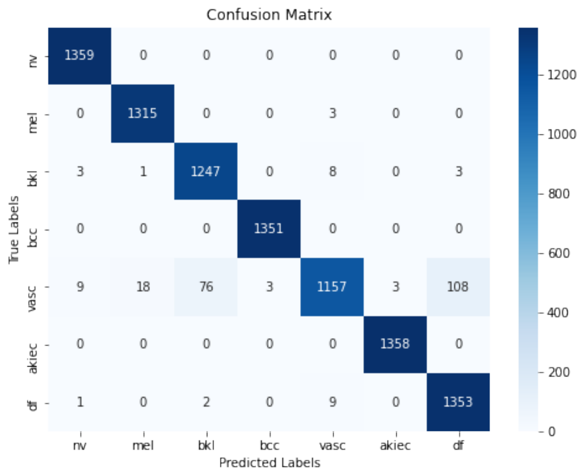

Figure 7. Multi-class confusion matrix of the customised CNN model

Table 4. Multi-class classification report of the customised CNN model

	Precision	Recall	F1-score	Support
0-nv	0,99	1,00	1,00	1359
1-mel	0,98	1,00	0,99	1318
2-bkl	0,96	0,98	0,97	1262
3-bcc	1,00	1,00	1,00	1351
4-vasc	0,99	0,88	0,93	1374
5-akiec	1,00	1,00	1,00	1358
6-df	0,94	0,99	0,97	1365
macro avg	0,98	0,98	0,98	9387
weighted avg	0,98	0,98	0,98	9387

Table 5. Metrics model

Metrics	Classification	
	Dense	SVM
Accuracy (%)	0,98	0,98
Precision (%)	0,98	0,98
Recall (%)	0,98	0,98
F1-score (%)	0,98	0,98

Table 6. CNN model learning results

	CNN model	
	Accuracy (%)	Loss (%)
Test set	0,98	0,19

The principal objective of this investigation was to examine the efficacy of deep learning algorithms in the classification of dermal lesions, with the results suggesting considerable promise for practical clinical implementation. This study highlights the critical role of employing sophisticated computational methodologies for the early identification and management of skin cancer, potentially resulting in enhanced patient outcomes and diminished healthcare expenditures. Nonetheless, several inquiries persist, particularly regarding the model's generalizability across diverse populations and the incorporation of these systems into clinical practice. Subsequent investigations ought to concentrate on mitigating these deficiencies and enhancing models for more extensive applicability. Through the integration of the findings presented in this study, we can facilitate the progression of innovative diagnostic instruments within the field of dermatology.

The evaluation of our proposed model against contemporary methodologies utilizing the HAM10000 dataset reveals its enhanced performance with respect to accuracy. As illustrated in Table 7 and Figures 8 and 9, which depict the accuracy and loss curves respectively, the proposed model attained an accuracy of 98%, thereby significantly surpassing multiple well-established architectures. For example, InceptionV3 and Xception, recognized for their strong feature extraction abilities, achieved accuracies of 91.56% and 91.47%, respectively. In a comparable analysis, InceptionResNetV2, recognized as a leading model in the field, achieved an accuracy of 93.20%, which remains significantly inferior to the performance metrics of the model we propose. Alternative methodologies, such as Shifted 2-Nets and EW-FCM+wide-shufflenet, demonstrated even lower accuracy rates, recording 83.20% and 84.80%, respectively. The findings underscore the effectiveness of the proposed methodology, demonstrating a significant enhancement compared to conventional techniques in the classification of dermatological images. The notable improvement in precision can be ascribed to the model's capacity to discern complex patterns and characteristics present in skin lesion images, thereby providing a viable approach for the accurate and dependable diagnosis of skin lesions.

Table 7. The proposed work with recent existing techniques on the HAM10000 dataset

Comparing proposed and existing work	Accuracy (%)
InceptionV3 [6]	91.56
InceptionResNetV2 [6]	93.20
Xception [6]	91.47
Shifted 2-Nets [27]	83.20
EW-FCM+wide-shufflenet [3]	84.80
Proposed model	98.00

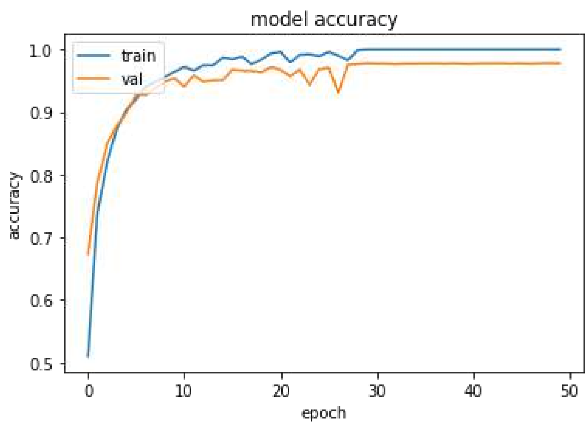

Figure 8. Accuracy of the customized CNN model

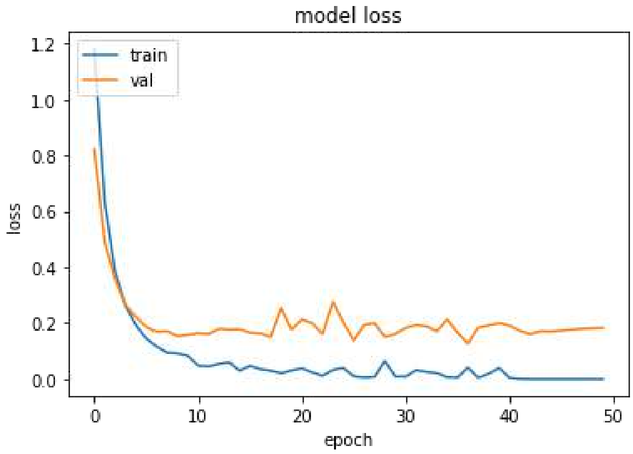

Figure 9. Loss of the customized CNN model

4. CHALLENGES AND LIMITATIONS

Deep learning models for dermatoscopic image analysis on edge devices present both opportunities and challenges. Real-time processing is possible but limited by computational power and memory. Optimizing these models is crucial for successful implementation. Establishing communication channels between edge devices and the cloud is challenging due to network latency, bandwidth constraints, and security protocols. The challenge is to maintain real-time responsiveness while ensuring uninterrupted data transmission. The multifaceted nature of edge devices and IoT platforms necessitates flexible and scalable solutions. Successful resolution of these challenges directly impacts the seamless integration of deep learning models into edge devices within the IoT framework, facilitating the development of decentralized and intelligent healthcare systems.

5. CONCLUSION

The study focuses on the use of CNNs to enhance dermatological diagnostics by classifying skin lesion images from the HAM10000 dataset. Achieving a 98% precision rate, the CNN model significantly outperformed traditional machine learning algorithms and previous methodologies. This performance was robust across metrics like accuracy, precision, recall, and F1-score, illustrating the model's effectiveness in identifying key features in dermatological images. While some may argue that traditional diagnostic methods are sufficient, our findings indicate that CNNs offer more accurate and standardized assessments, reducing diagnostic errors and improving patient outcomes. Although concerns about data requirements and implementation exist, advances in computational technology are making CNN-based solutions increasingly viable in clinical settings. Future research should focus on fine-tuning the model's hyper-parameters and exploring pre-trained CNN models to further enhance performance. Real-time image segmentation and improved categorization accuracy are essential for clinical applications, offering promising prospects for breakthroughs in dermatological care. By addressing these challenges, this research underscores the importance of continued innovation in applying deep learning technologies to medical imaging, with the potential to revolutionize dermatology and provide better patient outcomes globally.

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C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject administration
Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding acquisition
Fo	: **Fo**rmal analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data presented in this study are openly available in Harverd dataverse: [https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DBW86T].

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