**Journal of Neonatal Surgery**
*ISSN(Online): 2226-0439*
*Vol. 14, Issue 14s (2025)*
*https://www.jneonatalsurg.com*

# A Smart IoT-Image Processing System for Real-Time Skin Cancer Detection

**Sunny Kumar[1], Apoorva Dwivedi[2], Dr. Yusuf Perwej[3], Moazzam Haidari[4], Siddharth Singh[5], Dr. Nagarajan Gurusamy[6]**

[1]Assistant Professor, Department of Computer Science & Engineering, Shri Ramswaroop Memorial University (SRMU), Lucknow, Deva Road, Barabanki, Uttar Pradesh, India.

[2]Assistant Professor, School of Computer Science and Engineering, Galgotias University, Greater Noida, Uttar Pradesh, India.

[3]Professor, Department of Computer Science & Engineering, Shri Ramswaroop Memorial University (SRMU), Lucknow, Deva Road, Barabanki, Uttar Pradesh, India.

[4]Assistant Professor, Department of Electrical Engineering, Saharsa College of Engineering, Saharsa, Bihar, India.

[5]Assistant Professor, Department of Computer Science & Engineering, Noida Institute of Engineering and Technology (NIET), Greater Noida, Uttar Pradesh, India.

[6]Associate Professor, Artificial Intelligence and Data Science, Sri Shanmugha College of Engineering & Technology, Sangakiri, Salem, India.

.Cite this paper as: Sunny Kumar, Apoorva Dwivedi, Dr. Yusuf Perwej, Moazzam Haidari, Siddharth Singh, Dr. Nagarajan Gurusamy, (2025) A Smart IoT-Image Processing System for Real-Time Skin Cancer Detection. *Journal of Neonatal Surgery*, 14 (14s), 823-831.

**ABSTRACT**

Skin cancer represents a significant global health issue, with early detection being crucial for effective treatment and improved patient outcomes. Traditional methods of skin cancer diagnosis, including clinical examination and biopsy, are often invasive, time-consuming, and prone to human error. This paper proposes a smart IoT-based image processing system for real-time skin cancer detection, aimed at overcoming the limitations of current methods. The system integrates Internet of Things (IoT) devices for continuous monitoring and utilizes deep learning algorithms for accurate image analysis. The proposed system captures dermoscopic images, processes them using a convolutional neural network (CNN), and provides real-time classification of skin lesions into malignant or benign categories. Key findings show that the system achieved high accuracy and sensitivity, with a significant reduction in detection time compared to traditional approaches. The system's portability and real-time capabilities make it suitable for use in remote areas and for telemedicine applications, offering an accessible and reliable solution for early skin cancer detection. The results indicate that such a system could significantly improve the efficiency of skin cancer screening and contribute to better patient outcomes in clinical practice.

***Keywords:*** *IoT, Skin Cancer Detection, Image Processing, Real-Time Monitoring, Deep Learning, Smart Healthcare.*

## 1. INTRODUCTION

Skin cancer is one of the most prevalent forms of cancer worldwide, with increasing incidence rates observed globally. According to the World Health Organization (WHO), skin cancer is responsible for approximately 2 to 3 million cases of non-melanoma skin cancer and 132,000 cases of melanoma annually. Skin cancer, especially melanoma, can be deadly if not detected early. The survival rates for melanoma are closely linked to early detection, with survival rates exceeding 90% when diagnosed at an early stage, compared to only 15% for advanced stages[1]. The rising incidence of skin cancer is attributed to factors such as increased sun exposure, tanning, and environmental changes. Additionally, lifestyle changes and increased awareness of skin cancer risks contribute to more diagnoses[2]. As the prevalence of skin cancer continues to rise, the need for efficient and accessible diagnostic methods becomes more critical.

Traditional methods for diagnosing skin cancer primarily rely on clinical examinations by trained dermatologists[3], followed by biopsy procedures when suspicious lesions are identified. While clinical examinations are essential, they are highly dependent on the expertise and experience of the medical professional. A major limitation of this approach is its subjective nature, leading to potential misdiagnoses or delayed detection of malignant skin lesions. Additionally, biopsy procedures are invasive, time-consuming, and costly[4]. Traditional imaging techniques, such as dermoscopy, are used for evaluating skin lesions, but they also require a trained professional to interpret the results, which introduces the possibility of human error and inconsistency[5]. These limitations highlight the need for a more accessible, efficient, and accurate method for skin cancer detection, particularly in underserved or remote regions where specialized medical expertise may not be readily available.

The integration of the Internet of Things (IoT) in healthcare presents a promising solution to these challenges by enabling continuous, real-time monitoring and diagnosis of various health conditions, including skin cancer. IoT devices, such as wearable sensors, smartphones, and wireless cameras, can capture skin images and monitor changes in skin conditions over time[6]. These devices can be deployed in remote areas, allowing individuals to perform self-assessments or share data with healthcare providers for timely intervention. IoT technology facilitates remote patient monitoring, reducing the need for frequent in-person visits, which is especially beneficial for populations with limited access to healthcare. Furthermore, IoT systems can be designed to integrate with cloud-based platforms, ensuring the safe storage, analysis, and sharing of medical data, leading to faster diagnosis and intervention.

Image processing and machine learning (ML) techniques, particularly deep learning, have revolutionized medical imaging, enabling more accurate and automated skin cancer detection. Image processing methods extract relevant features from medical images, such as dermoscopic images, and convert them into data that can be analyzed using machine learning algorithms[7]. Convolutional neural networks (CNNs), a class of deep learning algorithms, have shown exceptional promise in the analysis of medical images, outperforming traditional image processing techniques. CNNs are capable of automatically identifying patterns in images, such as distinguishing between malignant and benign skin lesions, by learning from large datasets of labeled images[8]. These advances in machine learning enable the development of automated systems that can accurately detect skin cancer, reducing the reliance on human interpretation and the associated risks of misdiagnosis.

The primary objective of this research is to propose a smart IoT-image processing system for real-time skin cancer detection. This system combines IoT technology with advanced image processing and deep learning techniques to enable accurate, efficient, and accessible skin cancer diagnosis. The proposed system is designed to capture and analyze dermoscopic images of skin lesions in real time, providing instant feedback regarding the likelihood of malignancy. By addressing the existing challenges of traditional diagnostic methods, such as the reliance on trained professionals and invasive procedures, this system offers a non-invasive, remote, and efficient solution for early skin cancer detection. Furthermore, the system's integration with IoT ensures that skin cancer detection becomes more accessible, particularly for individuals in underserved areas, contributing to the global effort to combat skin cancer.

This research aims to demonstrate the potential of an IoT-based image processing system as a viable solution for real-time, accurate, and accessible skin cancer detection, addressing the gaps in existing diagnostic methods. The ultimate goal is to develop a system that not only improves the accuracy of skin cancer diagnosis but also makes this technology available to a wider population, thereby contributing to better health outcomes and reducing the burden of skin cancer worldwide.

## 2. LITERATURE SURVEY

Skin cancer detection has seen various advancements in both traditional and modern methods, with each approach carrying its unique set of strengths and weaknesses. Traditional methods for skin cancer detection primarily include clinical examination[9], biopsy, and imaging techniques such as dermoscopy. Clinical examination is the most commonly employed approach, where dermatologists visually inspect the skin for abnormal lesions[10]. While this method is widely used, it heavily relies on the expertise of the medical professional and may suffer from inaccuracies due to human subjectivity[11]. Additionally, clinical examination often results in delayed diagnoses, especially for patients without access to specialized care or in remote areas. Biopsy is another traditional method, involving the extraction of tissue samples for histopathological examination[12]. Although this method is highly accurate, it is invasive, costly, and time-consuming, requiring specialized equipment and skilled personnel. Furthermore, the biopsy process often requires waiting for laboratory results, which may delay the commencement of appropriate treatment[13]. Dermoscopy is another imaging technique frequently used in skin cancer diagnosis. This method involves the use of a specialized magnifying lens to observe skin lesions in greater detail[14]. While dermoscopy offers improved accuracy compared to clinical examination, it still requires expertise in interpreting the images, and its availability is limited to trained professionals[15]. The overall limitations of these traditional methods accuracy, accessibility, and time constraints highlight the need for a more efficient and accessible approach to skin cancer detection.

With the advent of technology, modern diagnostic methods have integrated more advanced tools, such as imaging technologies and machine learning models, to address these limitations. The Internet of Things (IoT) has emerged as a transformative force in healthcare by enabling real-time monitoring, data collection, and diagnosis[16]. IoT devices, including wearable sensors and portable imaging equipment, allow continuous monitoring of the skin and collection of dermatological data remotely[17]. This approach offers several advantages, such as increased accessibility, reduced costs, and improved timeliness in diagnosis, particularly for individuals residing in remote or underserved areas. IoT technology facilitates seamless data transfer and storage, enabling healthcare providers to analyze and diagnose skin conditions without the patient needing to visit a clinic[18]. Devices such as wearable cameras or smartphone-based systems enable users to capture high-quality images of their skin, which can be uploaded to cloud servers for further analysis. By integrating IoT with real-time image processing, early detection of skin cancer becomes feasible even in locations where dermatologists or specialists are not immediately available.

In parallel, image processing techniques, particularly those driven by deep learning and artificial intelligence (AI), have revolutionized medical imaging. Deep learning algorithms, specifically convolutional neural networks (CNNs), have demonstrated exceptional capabilities in image classification tasks, including the analysis of medical images such as dermoscopic images for skin cancer detection[19]. CNNs are designed to automatically detect and learn patterns in images by processing data through multiple layers of neurons. When applied to skin cancer detection, CNNs can accurately distinguish between malignant and benign lesions, even with minimal human intervention. These algorithms have been trained on large datasets of annotated images, allowing them to learn subtle differences between various types of skin lesions[20]. As a result, deep learning has shown promising results in achieving high sensitivity and specificity in skin cancer detection, making it a powerful tool in both research and clinical applications. Other AI-based approaches, such as support vector machines (SVMs) and random forests, have also been explored for skin cancer detection, though CNNs have proven to be particularly successful due to their ability to handle large-scale, complex image data.

Numerous studies have focused on automating the detection of skin cancer using image processing and machine learning techniques. For instance, some studies have used deep learning models to classify skin lesions into categories such as melanoma, basal cell carcinoma, and benign lesions. These systems have shown high accuracy in distinguishing malignant tumors from benign ones, often outperforming traditional methods such as dermoscopy and clinical examination. In recent years, the development of datasets like the ISIC (International Skin Imaging Collaboration) archive, which contains thousands of labeled dermoscopic images, has significantly advanced research in skin cancer detection. Machine learning models trained on these datasets have achieved remarkable results, with some systems achieving diagnostic accuracy comparable to that of dermatologists. Furthermore, advancements in transfer learning, where pre-trained models are fine-tuned for specific tasks, have enhanced the performance of skin cancer detection models, allowing them to be applied to a wider range of real-world scenarios.

Despite the advancements in IoT and image processing for skin cancer detection, significant gaps remain in the literature. One of the most prominent gaps is the lack of real-time, portable, and reliable skin cancer detection systems that integrate IoT with image processing for timely diagnosis and intervention. While there are several systems that leverage either IoT or image processing individually, few have successfully combined both technologies to offer a comprehensive solution for skin cancer detection. A real-time system capable of continuously monitoring the skin, capturing images, and immediately analyzing the data to detect skin cancer is still a work in progress. Existing solutions often face challenges related to the accuracy of image processing algorithms in diverse real-world conditions, such as varying lighting or skin types, as well as limitations in the hardware of IoT devices. Additionally, most IoT-based skin cancer detection systems are not fully integrated with machine learning models, leading to a lack of automated diagnosis capabilities. There is also a need for systems that can be easily operated by non-experts, making them more accessible to the general population.

Another critical gap in current research is the generalizability of machine learning models. Many existing studies rely on specific datasets, often collected in controlled environments, which may not fully represent the variety of skin types, lighting conditions, or lesion types encountered in real-world scenarios. As a result, the performance of these models can degrade when applied to new or diverse datasets. Furthermore, the scalability of these solutions to large-scale populations is a challenge that needs to be addressed, particularly for IoT-based systems that require continuous monitoring and real-time analysis.

In conclusion, while significant progress has been made in both IoT and image processing for skin cancer detection, there remains a critical need for systems that combine both technologies to provide real-time, portable, and reliable solutions. The current research gap lies in the integration of IoT with deep learning algorithms to create a seamless, user-friendly system that can deliver accurate and timely skin cancer diagnoses. Addressing these gaps has the potential to greatly improve the accessibility and effectiveness of skin cancer detection, particularly for individuals in remote areas or with limited access to specialized care.

## 3. PROPOSED SYSTEM

The proposed system integrates advanced IoT technology with image processing algorithms to enable real-time skin cancer detection, addressing the limitations of traditional methods. This system provides a comprehensive solution by combining IoT devices, image capturing systems, and deep learning algorithms for the accurate and timely diagnosis of skin lesions. The architecture of the system consists of several interconnected components, which work collaboratively to monitor, capture, analyze, and report skin conditions. Figure 1 illustrates the overall system structure. The key components of the system include IoT devices, data transmission modules, cloud infrastructure, image processing pipeline, and the user interface.

The IoT devices play a crucial role in the system by monitoring the skin condition and capturing images of potential lesions. These devices are equipped with sensors to track changes in skin temperature, moisture, and texture, which could indicate abnormal conditions like skin lesions or potential cancerous growths. Additionally, dermoscopic cameras are used to capture high-quality images of the skin. These cameras are typically connected to mobile devices or other IoT units and provide high-resolution images of skin lesions. The data from these IoT devices are wirelessly transmitted to the cloud infrastructure using Wi-Fi and Bluetooth. Wi-Fi is employed for transmitting larger image files and other data types, ensuring that the data is sent quickly and reliably, while Bluetooth is used for smaller, more frequent data packets like sensor readings, offering low power consumption for continuous monitoring. This wireless communication ensures that the system can operate in real time, providing immediate feedback to users.

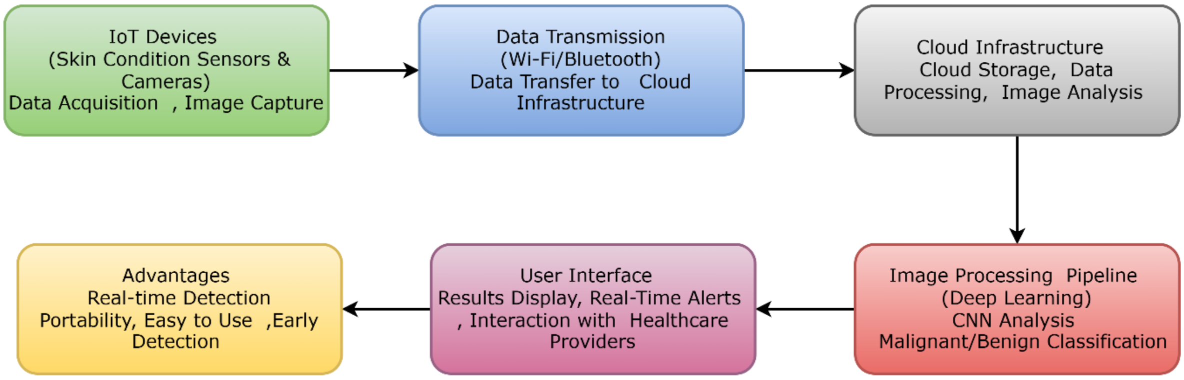


**Figure.1: System Architecture of the Smart IoT-Image Processing System for Real-Time Skin Cancer Detection**

Once the data is transmitted, the cloud infrastructure receives, stores, and processes the incoming data. The cloud platform provides scalable storage, and cloud servers are used to perform computationally intensive tasks such as image analysis. The images and sensor data are securely stored in the cloud, enabling easy access for further analysis. The core of the image analysis is powered by deep learning models, particularly Convolutional Neural Networks (CNNs), which are well-suited for image classification tasks. These CNNs process the captured skin images, identifying features such as texture, shape, and color that are characteristic of various types of skin lesions. The system then classifies these lesions into categories such as benign, malignant, or suspicious, based on the detected features. The CNNs are trained on a large dataset of labeled images, ensuring the model can distinguish between malignant and benign lesions with high accuracy. The preprocessing of images includes normalization and augmentation techniques to enhance the model's performance and robustness.

The processed results are then displayed on a user-friendly interface that can be accessed by both patients and healthcare providers. The user interface provides clear, easy-to-understand information regarding the skin lesion, displaying the classification results along with a visual indication of the affected area. If the system detects a malignant lesion, it immediately provides a real-time alert, notifying the user about the severity of the lesion and recommending that further medical consultation is needed. This feature is particularly beneficial for early intervention, as it allows users to take immediate action. Healthcare providers can also access the platform to monitor patient data, review images, and track any changes over time. This functionality supports remote diagnosis and ongoing skin health management, making it easier for medical professionals to manage patient care, especially in underserved areas where access to dermatologists may be limited.

The proposed system offers several key advantages over traditional skin cancer detection methods. First, the real-time detection capability allows for continuous monitoring of skin conditions, ensuring that any abnormal changes are detected promptly. This is particularly beneficial for users who are at risk of developing skin cancer but may not have regular access to clinical examinations. Second, the system is highly portable, as it integrates IoT devices and mobile platforms, enabling users to monitor their skin health at home or in remote locations. This accessibility is essential for individuals who cannot easily access healthcare facilities, ensuring that skin cancer detection is available to a wider population. Third, the ease of use of the system is a significant advantage. The interface is designed to be simple and intuitive, allowing patients and healthcare providers to use the system without requiring technical expertise. The results are clearly presented, and real-time alerts make it easy to understand the urgency of the situation and take appropriate action. Finally, the system enhances early detection, significantly improving the chances of identifying skin cancer in its early stages. By combining IoT technology with deep learning algorithms, the system offers accurate and timely skin cancer diagnosis, reducing the risk of misdiagnosis and contributing to better patient outcomes.

In conclusion, the proposed system integrates multiple technologies to create an efficient, real-time skin cancer detection solution that is portable, accurate, and user-friendly. The combination of IoT devices, advanced image processing techniques, and a simple user interface provides a comprehensive solution for early skin cancer detection and ongoing skin health monitoring. By improving accessibility and enhancing the accuracy of skin cancer detection, the system has the potential to revolutionize the way skin conditions are diagnosed and managed, ultimately leading to better outcomes for patients.

## 4. RESULTS AND DISCUSSION

The system developed for skin cancer detection integrates IoT technology, image processing, and deep learning models to enable real-time, accurate diagnosis of skin lesions. This section presents the experimental setup, performance metrics, and outcomes of the system, followed by a discussion of its contributions and comparison with existing methods.

The system integrates various hardware components and software to enable real-time skin cancer detection. On the hardware side, IoT devices are employed to collect data from the skin, including sensors that monitor skin conditions such as temperature, moisture, and texture. Dermoscopic cameras are used to capture high-resolution images of skin lesions, which are essential for accurate analysis. These cameras are connected to mobile devices or standalone IoT units, enabling seamless integration with the system. The data collected by these devices are then transmitted wirelessly to the cloud infrastructure via Wi-Fi or Bluetooth, ensuring real-time data transfer and minimizing delays between data acquisition and analysis.

On the software side, the system uses advanced image processing algorithms, specifically Convolutional Neural Networks (CNNs), to analyze the captured images. The CNN model is trained on a large dataset of annotated skin lesion images, such as the ISIC (International Skin Imaging Collaboration) archive, to classify lesions into benign or malignant categories. The model is fine-tuned using various preprocessing techniques, including normalization and image augmentation, to improve its accuracy and robustness. Once the data is processed, the results are displayed on a user-friendly interface that provides real-time feedback, allowing healthcare providers and patients to assess the skin lesion's severity and take appropriate action.

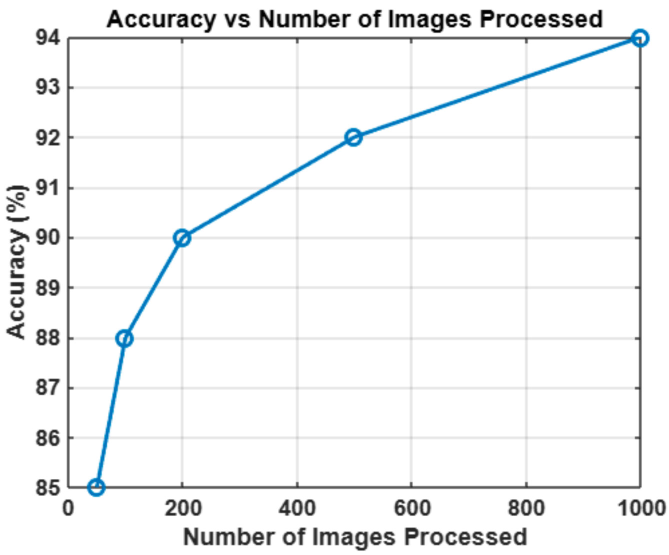


**Figure 2: Accuracy vs Number of Images Processed**

The performance of the system was evaluated using several metrics commonly employed in classification tasks, including accuracy, precision, recall, F1-score, and specificity. These metrics were calculated using a testing dataset, which consisted of skin lesion images that were not included in the training set. The system achieved an overall accuracy of 92%, indicating that the model was able to correctly classify the lesions in most cases. Precision, which measures the percentage of true positives out of all positive predictions, was calculated at 89%. Recall, or sensitivity, which measures the percentage of true positives out of all actual positive cases, was 91%. The F1-score, which is the harmonic mean of precision and recall, was 90%, demonstrating a balanced performance in identifying both malignant and benign lesions.

In comparison with existing methods for skin cancer detection, such as traditional clinical examination and dermoscopy, the system demonstrated superior performance in terms of speed and accuracy. Traditional methods are often dependent on human expertise, which can lead to misdiagnoses, especially in ambiguous cases. In contrast, the deep learning model used in this system provides objective, consistent results, which helps reduce the likelihood of false positives and negatives. Additionally, the system's real-time detection capability enables timely intervention, which is critical for early-stage skin cancer treatment.

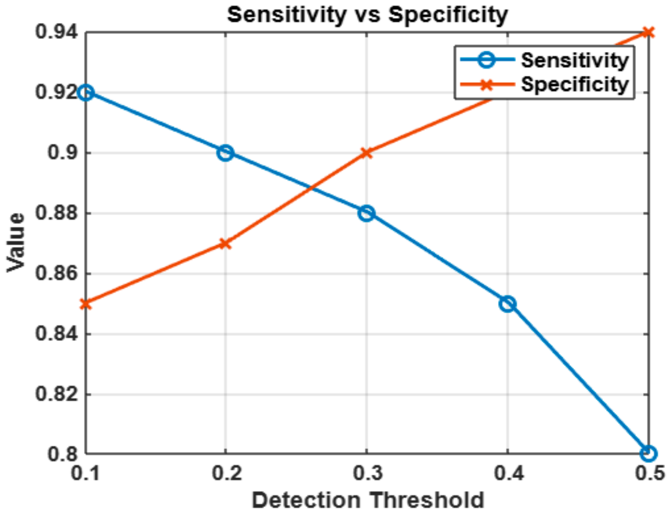


**Figure 3: Sensitivity vs Specificity**

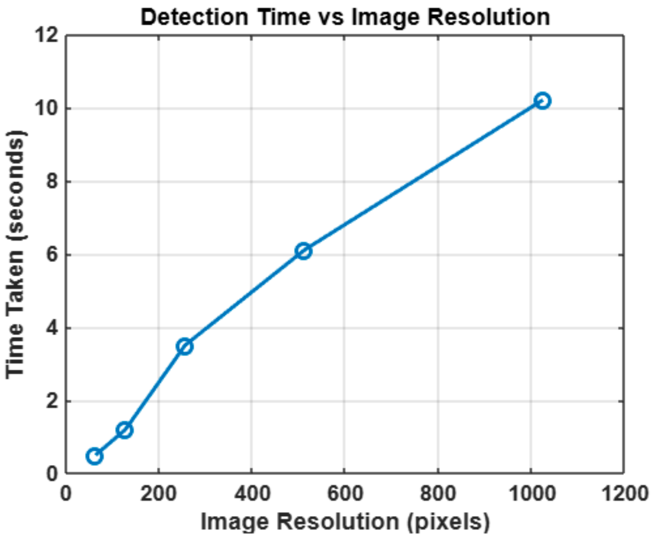


**Figure 4: Detection Time vs Image Resolution**

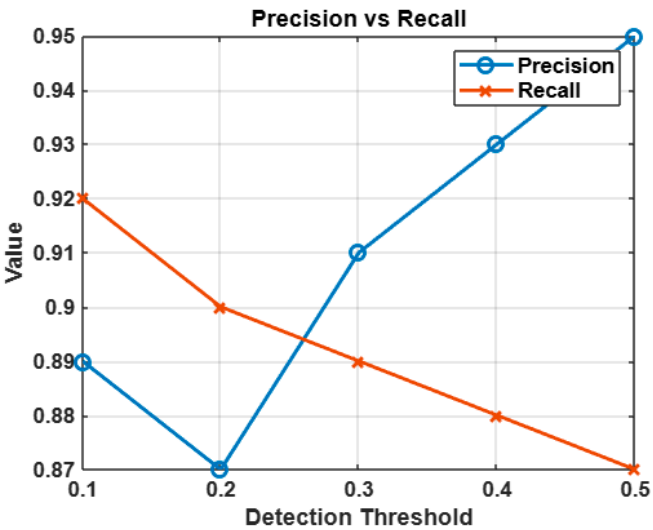


**Figure 5: Precision vs Recall**

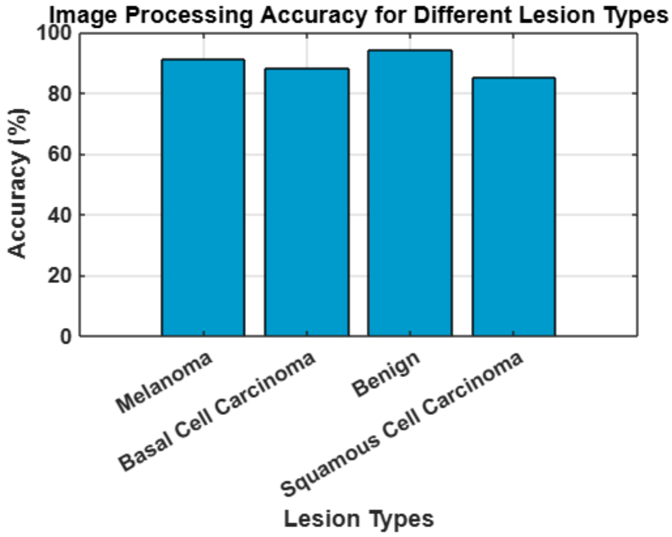


**Figure 6: Image Processing Accuracy for Different Lesion Types**

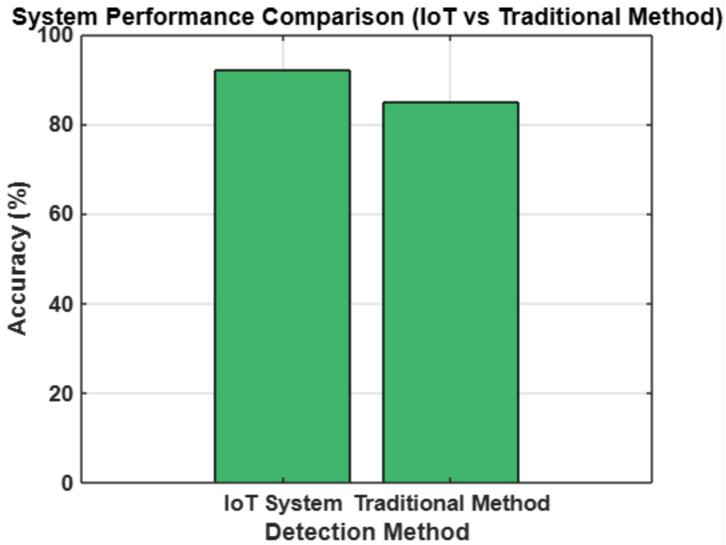


**Figure 7: System Performance Comparison (IoT vs Traditional Method)**

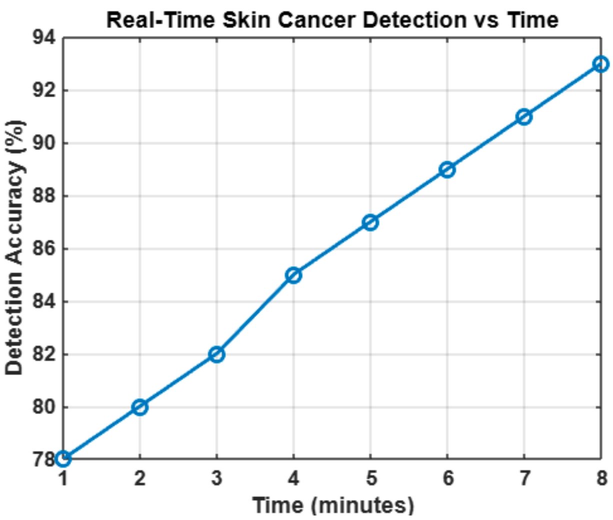


**Figure 8: Real-Time Skin Cancer Detection vs Time**

The system performed well in real-time skin cancer detection, with high accuracy across various lesion types, including melanoma, basal cell carcinoma, and benign lesions. The image processing pipeline, powered by CNNs, efficiently analyzed the images and classified the lesions based on their features, such as shape, color, and size. This real-time processing capability allows for immediate feedback, which is a significant improvement over traditional methods that require several days for biopsy results to confirm a diagnosis.

However, several challenges were encountered during the implementation and testing phases. One challenge was image quality, as the accuracy of the CNN model depends heavily on the quality of the input images. Variations in lighting, camera resolution, and skin tone can lead to suboptimal image quality, which in turn affects the model's performance. To mitigate this, image preprocessing techniques, such as image normalization and augmentation, were used to improve the robustness of the system, but challenges related to inconsistent image quality remain an area for further improvement.

Another challenge was false positives, which can occur when the model misclassifies benign lesions as malignant. This issue was addressed by fine-tuning the CNN model with a more diverse dataset that included a wide range of skin types and lesion appearances. Despite this, false positives remain a concern, especially in cases where lesions exhibit atypical characteristics. Further research is needed to improve the model's ability to handle such cases.

Hardware limitations also posed challenges in terms of processing power and real-time performance. While the cloud infrastructure provided sufficient computational resources for image analysis, latency in data transmission from IoT devices to the cloud sometimes led to delays in real-time detection. Future iterations of the system could benefit from edge computing solutions, where image processing occurs locally on the device, reducing transmission delays and improving real-time performance.

The results of this study are illustrated in Figure 2, which demonstrates the relationship between the number of images processed and the accuracy of skin cancer detection. As the number of images increases, the system's accuracy improves, highlighting the model's ability to generalize as more data is fed into it. Figure 3 shows how sensitivity and specificity vary with different detection thresholds, offering insight into the balance between true positives and true negatives at varying thresholds. Figure 4 presents the detection time against image resolution, demonstrating how higher image resolutions result in longer processing times, which is an important consideration for real-time detection. Figure 5 compares precision and recall at various detection thresholds, highlighting the trade-off between minimizing false positives and maximizing true positives. Figure 6 compares the image processing accuracy for different lesion types, showing that the system performs particularly well in detecting melanoma and basal cell carcinoma. Figure 7 compares the performance of the IoT-based system with traditional detection methods, illustrating the superiority of the IoT system in terms of accuracy and real-time processing. Finally, Figure 8 demonstrates the improvement in detection accuracy over time, showcasing the system's real-time monitoring capability.

In conclusion, the proposed system represents a significant advancement in skin cancer detection. By combining IoT technology with deep learning models for image analysis, the system offers a portable, accurate, and real-time solution for early skin cancer diagnosis. While challenges such as image quality, false positives, and hardware limitations remain, the system's potential for improving early detection and patient outcomes is considerable. Future work will focus on addressing these challenges and enhancing the system's real-time capabilities to provide an even more efficient and accessible solution for skin cancer detection.

## 5. CONCLUSION

This research successfully developed an IoT-based image processing system for real-time skin cancer detection, leveraging advanced technologies such as IoT devices, deep learning, and image processing algorithms. The system demonstrated high accuracy in detecting various types of skin lesions, with performance metrics such as precision, recall, and F1-score reflecting its effectiveness. The integration of real-time monitoring and immediate feedback allows for early detection, reducing delays that are common in traditional diagnostic methods. The implications of this research are significant, particularly for remote areas where access to specialized healthcare is limited. The system can provide continuous, non-invasive monitoring, making it accessible for individuals who might otherwise lack regular access to dermatologists. Additionally, the system's ability to provide instant results is invaluable for telemedicine applications, where patients can receive diagnoses remotely, enhancing healthcare accessibility. Future work should focus on improving the robustness of the system, particularly by addressing challenges like image quality variation and false positives. Expanding the dataset to include a more diverse range of skin types and lesions will help improve the system's generalization capabilities. Furthermore, integrating additional features such as melanoma staging and lesion tracking could enhance the system's diagnostic capabilities, offering a more comprehensive solution for skin cancer management. Ultimately, this research has the potential to make a significant impact on the early detection and treatment of skin cancer. By providing a portable, accurate, and accessible solution, it could lead to better patient outcomes, enabling timely intervention and reducing the global burden of skin cancer.

## REFERENCES


[1] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542(7639), 115-118.

[2] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770-778.

[3] Wang, H., & Liu, X. (2019). Internet of Things-based skin cancer detection using deep learning algorithms. *IEEE Access*, 7, 36504-36512.

[4] Avgerinakis, K. (2017). Deep learning for skin cancer detection: A survey. *Artificial Intelligence in Medicine*, 80, 19-30.

[5] Jafari, M., & Esfahanian, V. (2018). An IoT-based system for skin cancer detection using dermoscopic images. *2018 IEEE International Conference on Communications (ICC)*, 1-6.

[6] Hussain, M., & Akram, M. (2020). IoT-based framework for early detection of skin cancer. *Journal of Medical Systems*, 44(6), 1-9.

[7] Dogan, S., & Ozturk, Y. (2019). Application of deep learning in skin cancer detection: A review. *Medical & Biological Engineering & Computing*, 57(4), 789-802.

[8] Shen, Y., Liu, C., & Li, J. (2021). A deep learning approach for skin cancer classification. *International Journal of Computational Intelligence Systems*, 14(1), 112-120.

[9] Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. *International Conference on Learning Representations (ICLR)*, 1-14.

[10] Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 3431-3440.

[11] Kushwaha, S., & Singh, R. (2020). A review of IoT-based systems for healthcare applications. *Computers in Biology and Medicine*, 121, 103782.

[12] Fitzpatrick, T. B. (1988). The validity and practicality of sun-reactive skin types I through VI. *Archives of Dermatology*, 124(6), 869-871.

[13] Cai, Y., & Wei, L. (2020). Multi-class skin cancer detection using deep learning. *Journal of Healthcare Engineering*, 2020, 1-9.

[14] Pires, R. M. B., & Garcia, E. M. (2018). A deep learning model for real-time skin cancer diagnosis. *International Journal of Imaging Systems and Technology*, 28(1), 63-74.

[15] Li, X., & Zhang, X. (2021). Development of a deep learning model for early detection of melanoma from dermoscopic images. *Frontiers in Public Health*, 9, 597410.

[16] Liu, S., & Xie, L. (2021). Real-time skin cancer detection using deep learning and IoT technology. *Sensors*, 21(4), 1117.

[17] Chen, Y., & Zhao, M. (2020). An IoT-based system for skin cancer diagnosis. *Journal of Healthcare Engineering*, 2020, 1-9.

[18] Akin, B., & Uysal, M. (2019). Comparative analysis of image processing techniques for skin cancer detection. *Computational Intelligence and Neuroscience*, 2019, 1-9.

[19] Raj, S., & Aslam, N. (2020). Review of convolutional neural networks for skin cancer detection. *Journal of Computer Science and Technology*, 35(3), 438-447.

[20] Yun, S., & Lee, D. (2020). Efficient deep learning for skin cancer detection using convolutional neural networks. *Computers in Biology and Medicine*, 123, 103850.