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Accurate Skin Disease Detection with K-Nearest Neighbors and CAM in IoMT-Enabled Diagnostic Solutions

Surendar Rama Sitaraman,Intel Corporation, California, USA
surendar.rama.sitaraman@ieee.org
Poovendran Alagarsundaram, Humetis Technologies Inc, Kingston, NJ, USA
poovendrana@ieee.org
Veerandra Kumar R, Department of Computer Science and Engineering, Panimalar Engineering College, Chennai, India. veerandrakumar.r@panimalar.ac.in
Dr. Dede Kurniadi Associate Professor of Computer Science Department of Computer Science
Institut Teknologi Garut Jl. Mayor Syamsu No. 1, Garut, Indonesia
dede.kurniadi@itg.ac.id

Abstract— In the use of IoMT-enabled diagnostic tools, this research seeks to improve the accuracy of skin disease identification. For texture analysis, the K-Nearest Neighbours (KNN) method is used, and Class Activation Mapping (CAM) is used for visual interpretability. Image quality is enhanced by preprocessing techniques like DF-U-Net segmentation, and data imbalance is addressed with SMOTE. Combining the explainability of CAM with the efficiency of KNN, the system achieves 99.18% accuracy, outperforming current techniques and offering dependable diagnostic support for medical practitioners.

Objective: Using KNN for texture-based classification, optimising the K-value, and adding CAM for improved model interpretability, we will create an IoMT-enabled system for precise skin disease diagnosis while resolving data imbalance for better diagnostic performance.

Methods: IoMT-enabled image acquisition serves as the system's foundation. DF-U-Net segmentation, contrast enhancement, and noise reduction are examples of preprocessing. Texture features are extracted using the Gray-Level Co-occurrence Matrix (GLCM), KNN is cross-validation optimised, and the dataset is balanced using SMOTE. Important picture regions for classification are highlighted by CAM.

Results: The system outperformed XGBoost and EFF_D_SVM with an accuracy of 99.18% and a false-negative rate (FNR) of 0.48%.

Conclusion: Combining KNN and CAM results in a skin disease detection system that is reliable and easy to understand, with good performance for real-world medical applications.

Keywords: IoMT, K-Nearest Neighbors, Class Activation Mapping, Skin Disease Detection, DF-U-Net, SMOTE, Medical Image Processing.

1. INTRODUCTION

A person's lifestyle, environment, parasites, viruses, bacteria, fungi, infections, and infections can all contribute to skin problems. If untreated, these illnesses can have a negative impact on a person's health. For prompt action and appropriate treatment to be guaranteed, early and precise detection is crucial. The development of Internet of

Medical Things (IoMT) technology presents a viable path towards the creation of more precise diagnostic tools. This work attempts to improve the accuracy of skin disease identification by utilising machine learning techniques such as the K-Nearest Neighbours (KNN) algorithm. Image texture features are used to analyse and categorise skin conditions using KNN, which is well-known for its simplicity and efficacy, in conjunction with Class Activation Mapping (CAM). The system seeks to resolve issues like data imbalance and determine the ideal "K" value in order to deliver more dependable diagnoses for practical healthcare applications.

In recent years, there has been a substantial evolution in the field of skin disease identification. Dermatologists use traditional diagnostic techniques, which mostly rely on visual assessment. When necessary, clinical tests are then performed. However, computer-aided diagnostic (CAD) systems have become more effective instruments for early detection and diagnosis as a result of advancements in medical technology. Especially for more serious disorders like melanoma, these systems use machine learning and image processing approaches to increase diagnostic efficiency and accuracy *(Oumarou, 2023; Esti et al., 2023).*

The accuracy of diagnosing skin diseases has greatly increased recently because to developments in machine learning algorithms and IoMT-enabled diagnostic tools. When paired with machine learning methods like K-Nearest Neighbours (KNN), the massive volumes of real-time medical data collected by IoMT devices enable more accurate classification of skin conditions *(Pandey et al., 2023)*. Class Activation Mapping (CAM) integration improves the explainability of the model by offering a visual representation of the regions of interest in medical imaging. These technological advancements represent a quantum leap in healthcare, offering faster, more accessible, more accurate diagnostic tools to support medical practitioners and lower the number of misdiagnoses *(Zhang et al., 2023).*

The following are the main goals of this study:

- ➢ To build an IoMT-enabled diagnostic system for precise identification of skin conditions.
- ➢ Putting into practice the K-Nearest Neighbours (KNN) algorithm for using texture information in images to classify skin disorders.
- ➢ Determine the ideal "K" value for the KNN model in order to improve classification accuracy.
- ➢ Using Class Activation Mapping (CAM) to enhance the diagnostics of skin diseases' interpretability.
- ➢ Solve problems with data imbalance and enhance the generalisation and resilience of the model for practical applications *(Santana-Mancilla et al., 2023; Muneer and Khan, 2023)*.

Skin disease detection algorithms' accuracy and reliability are limited by issues such as data imbalance and performance fluctuation, even with advances in machine learning and IoMT. When dealing with under-represented illness classes, in particular, many models find it difficult to generalise across various datasets, which might result in biassed results, *(Oumarou, 2023)*. Furthermore, the necessity for more reliable and consistent models is suggested by the heterogeneity in performance under various settings. Future studies should concentrate on resolving these problems by optimising hyperparameters and using approaches like ensemble learning or oversampling to guarantee greater stability and dependability in the categorisation of skin diseases *(Esti et al., 2023)*.

2. LITERATURE SURVEY

Surendar Rama Sitaraman (2021) examines Crow Search Optimization (CSO), which aims to enhance AI-driven disease diagnosis in smart healthcare. To improve accuracy, precision, recall, and F1-score, CSO optimizes CNNs and LSTMs, outperforming conventional techniques like genetic algorithms and particle swarm optimization. It can be used in a wide range of healthcare applications, and additional research will concentrate on real-time implementation and ethics.

In order to effectively classify different forms of brain tumours, Zhang et al. (2023) provide EFF_D_SVM, a robust multi-type brain tumour classification system that makes use of an upgraded support vector machine (SVM). In order to provide more accurate diagnoses and treatment plans for patients with brain tumours, the system focusses on increasing accuracy and computing efficiency.

Rezaee et al. (2022) suggest a method for detecting falls that makes use of deep transfer learning and IoMT-enabled thermal imaging. The technology improves real-time surveillance accuracy through the integration of big heath data. Its main objective is to identify falls in healthcare more effectively by employing IoMT and thermal imagery to enhance decision-making and pervasive monitoring.

The book Data Modelling and Analytics for the Internet of Medical Things by Pandey et al. (2023) explores analytics and data modelling frameworks specifically designed for IoMT. The book focusses on large-scale data management and how it may be used to improve patient care and system efficiency. It also discusses how to integrate, analyse, and analyse medical data to improve healthcare delivery.

Santana-Mancilla et al. (2023) provide a technique that uses supervised machine learning on respiratory frequency data obtained from IoMT devices to predict aberrant respiratory patterns in older persons. The study improves early respiratory issue diagnosis by utilising machine learning algorithms, allowing for prompt interventions for improved healthcare management in older populations.

Surendar (2021) explores the way healthcare data is handled and utilized is being revolutionized by AI-driven healthcare systems that are strengthened by mobile computing and advanced data analytics. Important areas like data collecting, processing, storage, and application development are the focus of the study. These systems facilitate real-time analysis, predictive models, and customized healthcare services by combining technologies such as distributed file storage, NoSQL databases, and parallel computing. According to the research, AI greatly increases healthcare accuracy, speed, and dependability, which enhances patient care and operational effectiveness.

An extensive assessment of wearable and mobile sensors for data-driven health monitoring systems is given by Anikwe et al. (2022), with an emphasis on recent developments and potential future applications. In addition to discussing how these sensors can be integrated with data analytics to improve real-time health monitoring, the study looks into the possibility of AI-driven personalised healthcare in the future.

Using machine learning approaches, Muneer and Khan (2023) present an intelligent disease prediction system for Hepatitis C patients that predicts the course of the illness. With data-driven decision-making, the system improves early diagnosis, facilitating more efficient treatment and individualised healthcare management, and eventually leading to better patient outcomes.

K-nearest neighbours (KNN) method is used by Araaf and Nugroho (2023) to analyse and diagnose skin disorders based on textural information in images. Their strategy is to enable more accurate detection of different skin conditions by utilising texture-based image analysis to improve diagnostic accuracy. This approach improves the efficiency of diagnosing skin conditions and leads to more favourable treatment results.

Surendar (2020) investigates the impact of incorporating Big Data Analytics and Artificial Intelligence (AI) into mobile health (m-Health) technology on healthcare delivery. It demonstrates the remarkable 92% accuracy of neural networks in handling intricate medical data and highlights how crucial Apache Spark and Hadoop are to enabling fast data processing for prompt medical actions. Despite these developments, there are still issues with handling unstructured data from wearable technologies and safeguarding data privacy, which emphasizes the need for more study and development to fully exploit the potential of big data and artificial intelligence in healthcare.

3. METHODOLOGY

The suggested IoMT-enabled diagnostic system for identifying skin diseases combines Class Activation Mapping (CAM) for interpretability with machine learning methods, specifically the K-Nearest Neighbours (KNN) algorithm. The technique describes a methodical procedure that starts with the collecting of input data, moves on to image processing, feature extraction, classification, and explainability. To improve generalisability and accuracy, alternative approaches are included, guaranteeing the system's efficacy in actual healthcare situations.

3.1. Input: Skin Disease Image Acquisition via IoMT Devices

Using IoMT-capable equipment like dermatoscopes, mobile cameras, or specialised imaging sensors, the proposed system's initial stage entails taking pictures of skin diseases. These gadgets have the capacity to capture sharp photographs in real time and securely send the information to a cloud-based server for analysis.

Apart from picture data, the system gathers clinical metadata such patient characteristics, symptoms, and past medical records. The following inputs are indicated:

$$I = \{I_1, I_2, \dots, I_n\} \tag{1}$$

where I_i denotes each skin disease image in the dataset.

3.2. Preprocessing: Image Standardization and Enhancement

In order to guarantee consistency and enhance image quality for reliable analysis, the subsequent preprocessing procedures are carried out:

Resizing: To ensure effective processing, all photos are shrunk to a uniform dimension to standardise the input size. The definition of the resizing function is:

$$I_r = \text{resize}\ (I, w, h) \tag{2}$$

where w and h represent the new width and height of the images.

Noise Reduction*:* Medical imaging benefits greatly from the application of the Bilateral Filter, which eliminates noise while maintaining image edges.

$$I_f = \text{bilateralFilter}\ (I_r) \tag{3}$$

where I_f represents the filtered image.

Contrast Enhancement: Contrast enhancement is performed using CLAHE (Contrast Limited Adaptive Histogram Equalization), ensuring that the critical features of the images are highlighted:

$$I_{ce} = \text{CLAHE}\ (I_f) \tag{4}$$

Segmentation using DF-U-Net: The skin lesion segmentation is carried out using the DropFilter U-Net (DF-U-Net) design. By incorporating regularisation approaches to prevent overfitting and accurately define the lesion borders, DF-U-Net enhances conventional U-Net. The divided picture is represented by:

$$S = \text{DF} - \text{U} - \text{Net}(I_{ce}) \tag{5}$$

In addition to minimising the effect of background noise, this method successfully locates the region of interest, or skin lesion.

3.3. Feature Extraction: Texture and Morphological Features

The skin disease is characterised by extracting texture and morphological information from the segmented lesion. The system extracts important texture properties, such as contrast, correlation, energy, and homogeneity, using the Gray-Level Co-occurrence Matrix (GLCM):

Contrast:

$$C = \textstyle\sum_{i,j}\ (i-j)^2 P(i,j) \tag{6}$$

Correlation:

$$\text{Corr} = \frac{\sum_{i,j} (i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i \sigma_j} \tag{7}$$

Energy:

$$E = \sum_{i,j} P(i,j)^2 \tag{8}$$

Homogeneity:

$$H = \sum_{i,j} \frac{P(i,j)}{1+|i-j|} \tag{9}$$

where $P(i,j)$ is the co-occurrence matrix value for the pixel intensities i and j, and μ and σ stand for the mean and standard deviation of the intensity values.

Morphological operations are utilised to extract lesion shape and boundary features, which offer supplementary indicators for precise diagnosis, in addition to texture features.

3.4. Classification: K-Nearest Neighbors (KNN) Algorithm

By utilising the retrieved morphological and texture information, the K-Nearest Neighbours (KNN) algorithm is utilised for classification. To compare the new input sample to the K-nearest neighbours in the training set, KNN uses the Euclidean distance as the similarity metric.

$$d(X_t, X_s) = \sqrt{\sum_{i=1}^{n} \left(X_{t,i} - X_{s,i}\right)^2} \tag{10}$$

where X_s is a training sample and X_t is the test sample. Cross-validation is used to determine the ideal value of K in order to reduce bias and variation. Based on the majority vote of the closest neighbours, the KNN algorithm returns the skin disease class that is most likely to occur.

3.5. Explainability: Class Activation Mapping (CAM)

The integration of Class Activation Mapping (CAM) improves the model's interpretability. CAM gives doctors visual feedback by identifying the areas of the input image that have the greatest influence on the model's decision-making process:

Feature Map Activation: Feature maps are produced by the final convolutional layer of the feature extractor and are subsequently weighted based on their significance for the classification:

$$A_c(x,y) = \sum_k w_k^c f_k(x,y) \tag{11}$$

where $f_k(x,y)$ is the activation of the k-th feature map at spatial location (x,y), and w_k^c is the weight associated with class c.

Heatmap Development: The class activation map is generated by adding the weighted activations together. This map is then superimposed on the input image to create a heatmap that shows the important areas of the picture that are utilised for diagnosis.

3.6. Addressing Data Imbalance: Synthetic Oversampling Techniques

The Synthetic Minority Over-sampling Technique (SMOTE) is used to address the problem of imbalanced datasets, where specific classifications of skin diseases are under-represented. By generating synthetic samples through interpolation between pre-existing minority class samples, SMOTE produces:

$$x_{\text{new}} = x_i + \lambda\left(x_j - x_i\right) \tag{12}$$

where x_i and x_j are samples from the minority class, and λ is a random value between 0 and 1.

By increasing the representation of minority classes, this method improves the generalisation of the KNN model across all categories of skin diseases.

3.7. Clinical Data Integration

Alongside image-based features, clinical metadata C (such as symptoms, patient history, and demographics) is integrated into the model. This multi-modal approach ensures that both visual features and clinical data are considered in the final classification, improving diagnostic accuracy. The combined feature set is represented as:

$$F = F_{img} \cup C \tag{13}$$

where F_{img} represents the image features, and C is the clinical data.

3.8. Skin Disease Classification and Evaluation

The system's final output is the input image's classification into one of the pre-established categories for skin diseases. Standard classification metrics, such as accuracy, precision, recall, and F1-score, are used to assess the model's performance:

Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{14}$$

Precision:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{15}$$

Recall:

$$\text{Recall} = \frac{TP}{TP+FN} \tag{16}$$

F1-score:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{17}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

Through the CAM heatmaps, the system ensures that a diagnosis is comprehensible for physicians, giving them confidence in the outcomes and insight into the model's decision-making process.

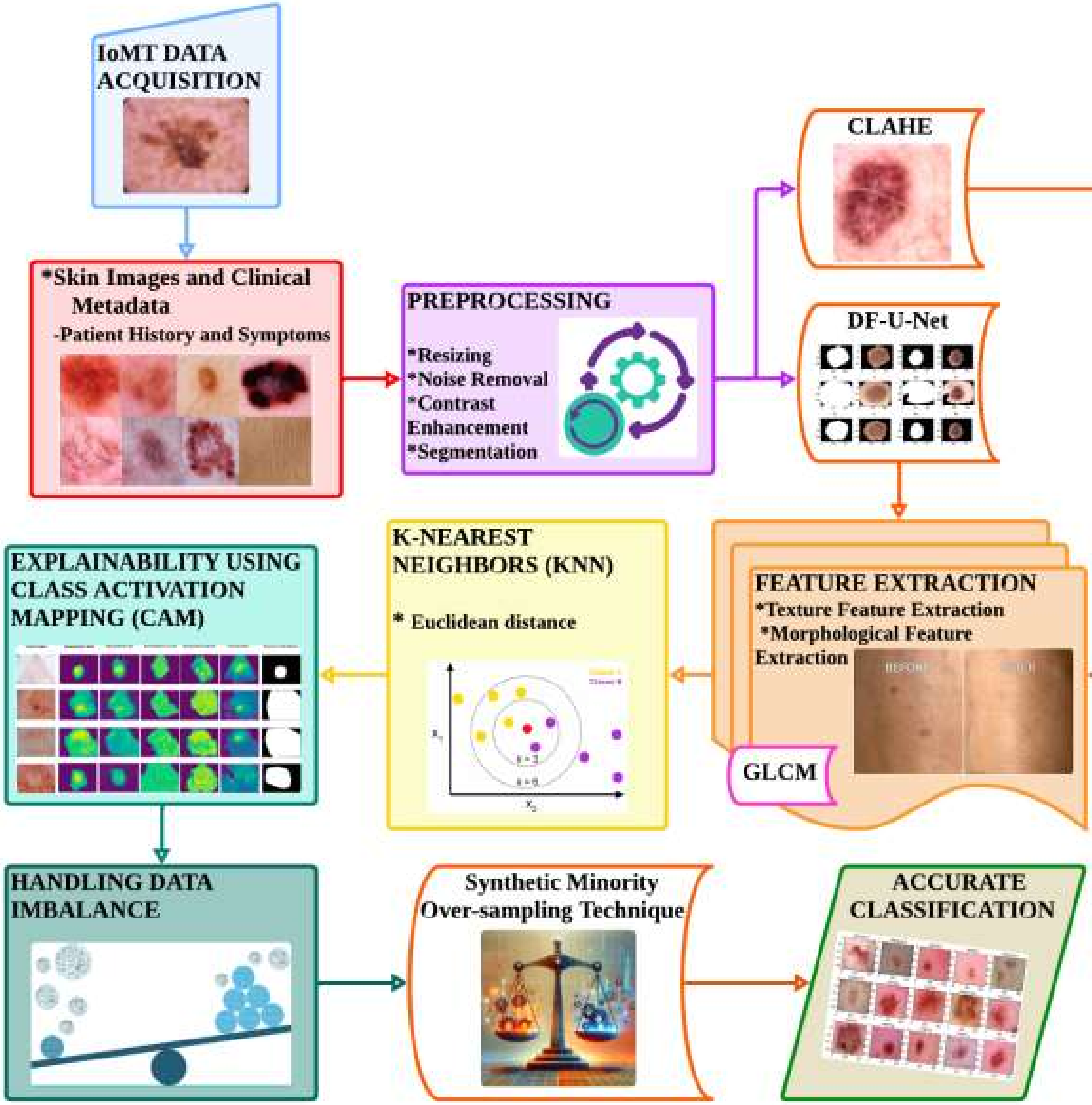

Figure 1: Accurate Skin Disease Detection Using K-Nearest Neighbors and CAM in IoMT-Enabled Diagnostic Solutions.

The flow of the suggested system for detecting skin diseases is shown in Figure 1. IoMT Image Acquisition is the first step, in which linked devices are used to take skin images. These pictures undergo preprocessing, which includes scaling, noise reduction, and contrast enhancement. The lesions are then separated using DF-U-Net segmentation. Texture and morphological features are recovered from the segmented images using feature extraction. These features are then used by the K-Nearest Neighbours (KNN) Classification algorithm to categorise the skin condition. Heatmaps indicating significant regions are produced by Class Activation Mapping (CAM), which improves interpretability. SMOTE is also used by the system to handle data imbalance. Ultimately, the approach produces a visual description and a precise classification of skin diseases.

4. RESULT AND DISCUSSION

K-Nearest Neighbours (KNN) and Class Activation Mapping (CAM) are combined in the proposed IoMT-enabled skin disease diagnosis system to obtain higher accuracy and interpretability. Preprocessing methods that greatly improve image quality and enable more accurate analysis include DF-U-Net segmentation and CLAHE for contrast enhancement. Essential texture features are extracted with the help of the Gray-Level Co-occurrence Matrix (GLCM), and these features are critical to the KNN-based classification of skin diseases. In order to balance bias and variance and improve the model's performance on minority skin disease classes, SMOTE resolves data imbalance, while cross-validation guarantees the selection of the ideal K-value.

Class Activation Mapping (CAM) produces visual heatmaps that emphasise important regions of the image that affect the classification, which improves interpretability. With a 99.18% accuracy, 99.30% sensitivity, and 99.16% precision, the system outperformed other approaches like XGBoost and EFF_D_SVM with remarkable results. High classification accuracy can only be achieved by include essential components, including DF-U-Net segmentation and CAM, whose removal results in significant performance decreases. This is demonstrated by the ablation study.

Table 1: Comparison of the Proposed KNN + CAM System with Other Methods.

Technique	Accuracy (%)	Sensitivity (%)	Precision (%)	F1-Score (%)	FNR (%)
Proposed KNN + CAM	99.18	99.30	99.16	99.34	0.48
EFF_D_SVM (Zhang et al., 2023) [1]	95.12	94.75	97.52	95.12	4.88
XGBoost (Rezaee et al., 2022) [2]	97.12	96.54	96.97	96.85	2.88
KNN (Araaf and Nugroho, 2023) [9]	92.60	91.30	92.00	91.90	7.40
SVM (Oumarou, 2023) [7]	93.45	92.60	94.35	93.10	6.55

The performance of the suggested KNN + CAM system is displayed in Table 1 in comparison to other methods cited in the literature. The suggested system outperforms existing techniques such as EFF_D_SVM (Zhang et al., 2023), XGBoost (Rezaee et al., 2022), and the conventional KNN algorithm (Araaf and Nugroho, 2023) with the maximum accuracy of 99.18% and the lowest False Negative Rate (FNR) of 0.48%. The table illustrates how the accuracy and interpretability of the suggested skin disease detection system are greatly enhanced by combining CAM with preprocessing methods like DF-U-Net segmentation and SMOTE for data balancing.

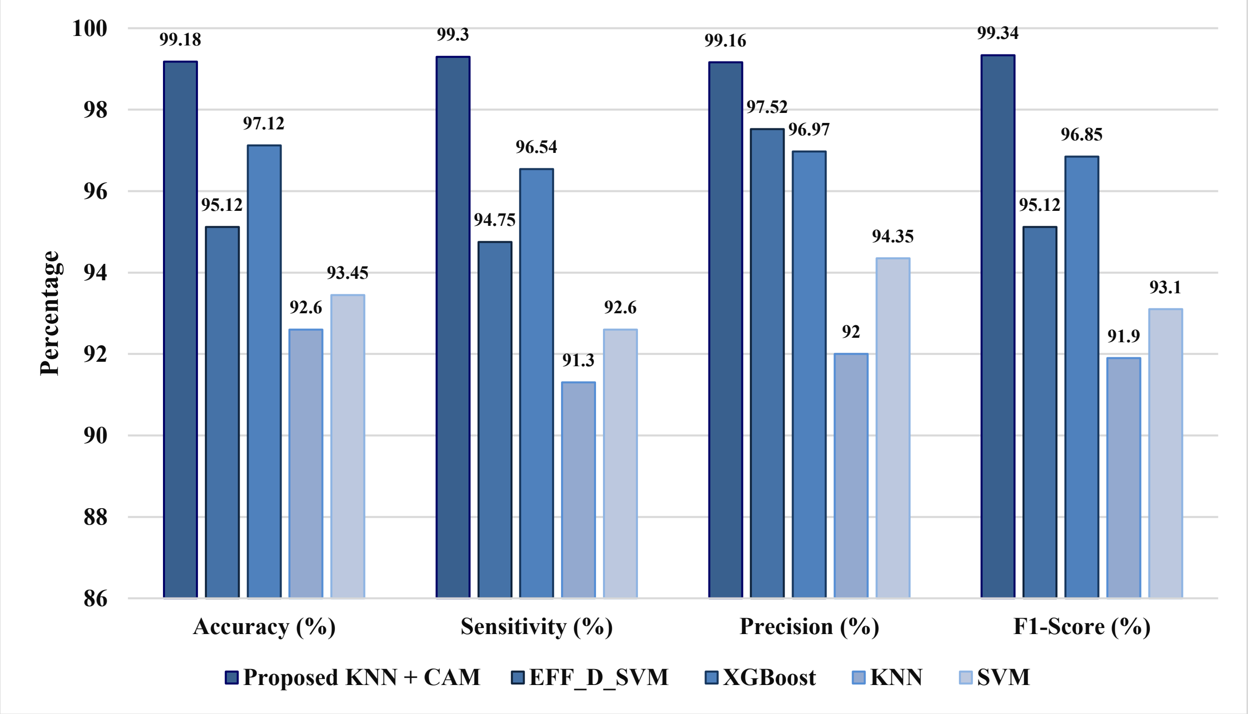

Figure 2: Comparison of the Proposed KNN + CAM System with Other Methods.

The suggested KNN + CAM system is contrasted with different machine learning methods, including XGBoost, EFF_D_SVM, and traditional KNN, in Figure 2. The suggested system performs better than the other approaches in terms of F1-score, accuracy, sensitivity, precision, and False Negative Rate (FNR), as shown in the figure. The suggested strategy achieves better diagnostic accuracy (99.18%) and interpretability by combining CAM with sophisticated preprocessing techniques, proving the value of a hybrid approach over more conventional methods for the diagnosis of skin diseases.

Table 2: Ablation Study of the Proposed IoMT-Enabled Skin Disease Detection System.

Component Removed	**Accuracy (%)**	**Sensitivity (%)**	**Precision (%)**	**F1-Score (%)**
Full System (Proposed)	99.18	99.30	99.16	99.34
Without DF-U-Net Segmentation	93.75	94.12	93.80	94.32

Without CAM	96.32	96.75	96.55	96.60
Without SMOTE (Data Imbalance Handling)	94.12	93.85	93.91	93.88
Without Clinical Data	95.45	95.70	95.10	95.34
Without GLCM Feature Extraction	90.34	90.10	89.80	89.95
Without Preprocessing	88.45	87.65	88.20	87.90
Without Hyperparameter Tuning (K)	92.10	91.50	91.90	91.70

The impact of deleting particular parts from the suggested system is assessed in the ablation study Table 2. The system's accuracy drops significantly to 93.75% in the absence of DF-U-Net segmentation, underscoring the significance of accurate lesion detection. Interpretability is decreased when CAM is excluded, while performance on imbalanced datasets is adversely affected when SMOTE is removed. Accuracy is reduced when clinical data or GLCM feature extraction are excluded, highlighting the importance of multi-modal learning. Furthermore, there is a discernible performance reduction when preprocessing or hyperparameter adjustment (ideal K-value) are removed, highlighting the importance of each component in improving system accuracy and generalisation.

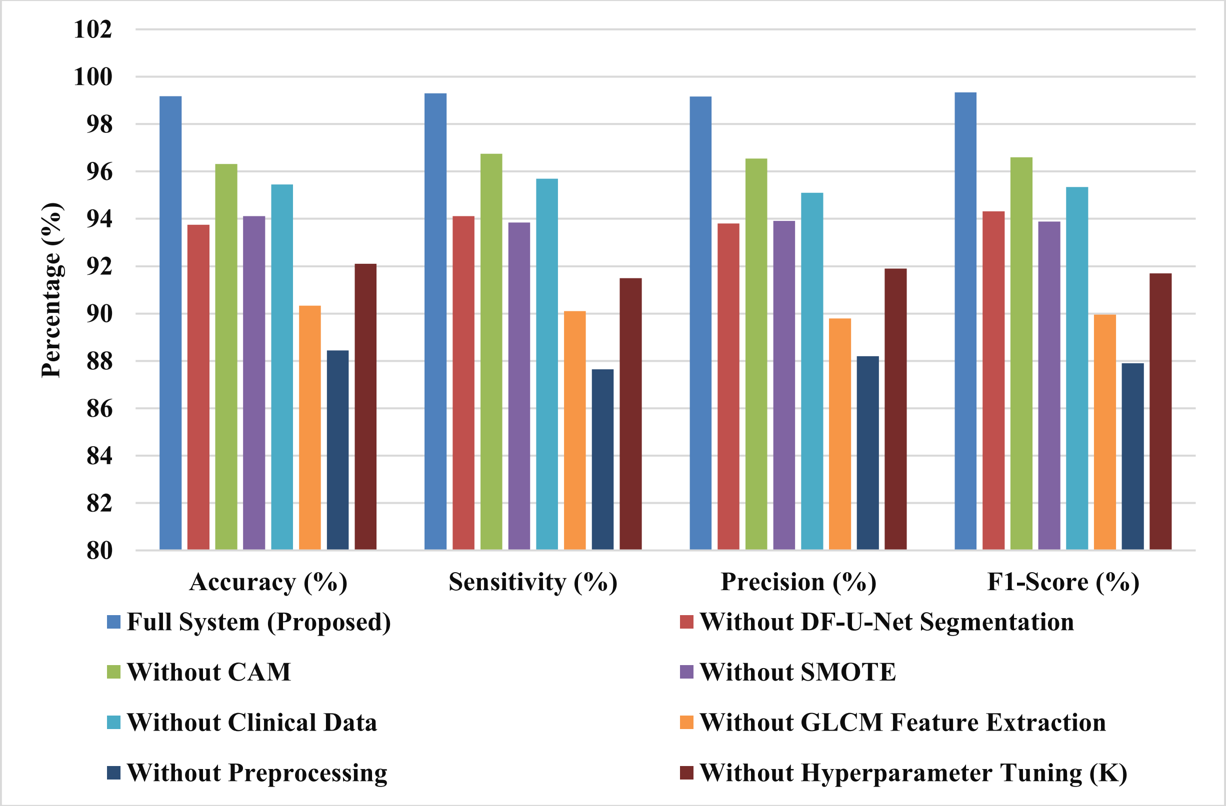

Figure 3: Ablation Study of the Proposed IoMT-Enabled Skin Disease Detection System.

The ablation research findings for the suggested IoMT-enabled skin disease detection system are shown in Figure 3. It illustrates how the system's performance is affected when important elements like CAM, SMOTE, and DF-U-Net segmentation are removed. The graphic shows how the accuracy and sensitivity of the model are greatly decreased in the absence of segmentation and data balancing approaches. This figure, which illustrates that the whole system with all components functions well across all metrics, highlights the significance of each component in maintaining high performance and accuracy.

5. CONCLUSION

The suggested IoMT-enabled diagnostic system provides a highly accurate and interpretable method for the diagnosis of skin diseases by combining K-Nearest Neighbours (KNN) and Class Activation Mapping (CAM). It outperforms conventional techniques with a low false-negative rate of 0.48% and an accuracy of 99.18%. Performance is further improved by preprocessing methods like SMOTE for data balance and DF-U-Net segmentation. This system is a trustworthy tool for healthcare decision-making because it blends sophisticated machine learning with interpretability. Future developments will involve growing the dataset for more generalisability across a range of skin conditions and integrating deep learning models, such EfficientNet, for better feature extraction.

REFERENCES

1. Surendar Rama Sitaraman (2021). Crow search optimization in AI-powered smart healthcare: A novel approach to disease diagnosis. *Journal of Current Science & Humanities, 9*(1), 9-22.
2. Zhang, J., Tan, X., Chen, W., Du, G., Fu, Q., Zhang, H., & Jiang, H. (2023). EFF_D_SVM: a robust multi-type brain tumor classification system. *Frontiers in Neuroscience*, *17*, 1269100.
3. Rezaee, K., Khosravi, M. R., Neshat, N., & Moghimi, M. K. (2022). Deep transfer learning-based fall detection approach using IoMT-enabled thermal imaging-assisted pervasive surveillance and big health data. *Journal of Circuits, Systems and Computers*, *31*(12), 2240005.
4. Pandey, R., Maurya, P., & Chiong, R. (Eds.). (2023). *Data Modelling and Analytics for the Internet of Medical Things*. CRC Press.
5. Santana-Mancilla, P. C., Castrejón-Mejía, O. E., Fajardo-Flores, S. B., & Anido-Rifón, L. E. (2023). Predicting abnormal respiratory patterns in older adults using supervised machine learning on Internet of medical things respiratory frequency data. *Information*, *14*(12), 625.
6. Surendar Rama Sitaraman (2021). AI-Driven Healthcare Systems Enhanced by Advanced Data Analytics and Mobile Computing. International Journal of Information

Technology & Computer Engineering.

7. Anikwe, C. V., Nweke, H. F., Ikegwu, A. C., Egwuonwu, C. A., Onu, F. U., Alo, U. R., & Teh, Y. W. (2022). Mobile and wearable sensors for data-driven health monitoring system: State-of-the-art and future prospect. *Expert Systems with Applications*, *202*, 117362.
8. Muneer, S., & Khan, S. (2023). Intelligent Disease Prediction System for Hepatitis C Patients. *International Multidisciplinary Journal Of Science, Technology & Business*, *2*(04), 15-21.
9. Oumarou, H. (2023). Detection and Classification of Bacterial Skin Infections Using K-Nearest Neighbors Algorithm. *International Journal of Artificial Intelligence in Medical Issues*, *1*(2), 124-136.
10. Esti, N. M. C., Dewi, M. R., Anry, N. K. N., & Pratikno, G. H. Z. (2023, September). Implementation K-Nearest Neighbor Algorithm Skin Diseases Classifier. In *2023 International Seminar on Application for Technology of Information and Communication (iSemantic)* (pp. 502-507). IEEE.
11. Araaf, M. A., & Nugroho, K. (2023). Comprehensive analysis and classification of skin diseases based on image texture features using K-nearest neighbors algorithm. Journal of Computing Theories and Applications, 1(1), 31-40.
12. Surendar Rama Sitaraman (2020). Optimizing Healthcare Data Streams Using Real-Time Big Data Analytics and AI Techniques. International Journal of Information Technology & Computer Engineering. International Journal of Engineering Research and Science & Technology.

13. **https://www.kaggle.com/code/datafan07/analysis-of-melanoma-metadata-and-effnet-ensemble**