Enhanced KNN-Based Model for Early Detection and Classification of Skin Cancer

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Abstract

Skin cancer especially melanoma is one of the most aggressive and lethal type of cancer in the world allied with the fact that early detection is a major step towards survival. Nevertheless, it has been difficult to distinguish benign and malignant skin lesions because they are visually similar. The present paper identifies a modified K-Nearest Neighbors (KNN) classification model that is expected to correct skin cancer diagnosis without false negatives, as the classification model makes the determination by means of machine learning on digital pictures of skin lesions. The five principal components include the steps in the model, namely data acquisition, preprocessing, feature extraction, classification, and evaluation, and its priority is to maximize the accuracy of the diagnosis. As shown in the proposed KNN model, feature extraction techniques aka Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) are used to extract the valuable features texture, shape, and edges of the image. It was found that the KNN model is superior to both the traditional and deep learning models with overall accuracy at 92.4%, which is higher than 89.4% of dermatologists and 81.5% of ResNet models. Furthermore, due to the low CPU-intensive requirements of the KNN model, the latter solution is viable in resource-limited settings providing a non-invasive and highly dependable method of screening individuals at risk of early-stage skin cancer. The results indicate that the more robust KNN model would become a benefit to dermatologists in terms of improved diagnostics and eliminated invasive procedures opportunities. Additional studies are required to determine feasibility of adaptation to the real-life setting and clinician use.

Keywords

Artificial Intelligence, Cancer, Classification, Machine Learning, KNN, SDG, ResNet

1. Introduction

Cancer is one of the most prevalent diseases in terms of the costs associated with medical care. According to the most recent projections, around 10 million people will lose their lives to cancer by the year 2020 [1]. The most common types of cancer to be diagnosed are lung cancer, breast cancer in women, and prostate cancer in men. Malignancies of the lung, liver, and stomach account for the majority of fatalities attributable to cancer [2]. The risk of developing skin cancer, including malignant melanoma as well as non-melanoma skin cancers, is significantly higher among Caucasians (NMSC). In the United States of America, more people are diagnosed with skin cancer each year than any other type of cancer [3].

Melanoma is the most aggressive and potentially fatal form of skin cancer, as in figure 1. If detected at an early enough stage, surgical treatment may be an option for a cure. Survival rates are significantly reduced whenever metastasis is evident. Melanoma can only be diagnosed once a patient has undergone a clinical exam and had a lesion biopsied, both of which must reveal certain specific features [4]. Non-Hodgkin lymphomas can take several forms, including squamous cell carcinoma and basal cell carcinoma, for instance. The prognosis and outcome of skin cancer patients are significantly improved when preventative care and early detection are provided [5]. Visual inspection alone might not be sufficient to differentiate between benign and malignant tumours. The procedure that is regarded as the gold standard is known as histopathology analysis of a skin sample [6]. When performing a skin biopsy, the process is invasive and uncomfortable. In addition, many samples may need to be taken in cases where the lesions have varying outward manifestations. The diagnosis of disease can also benefit from the application of diagnostic models that do not involve the use of intrusive procedures [7,8]. Because of knowledge gaps, high costs, and limited availability, it will be challenging to see widespread adoption of these technologies in the near future. Numerous scientific and technological advancements have made it possible to develop a number of imaging techniques that do not involve the use of invasive procedures in order to identify melanoma. Discussion is currently taking place over potential approaches to the detection of melanoma and other forms of skin cancer [9].

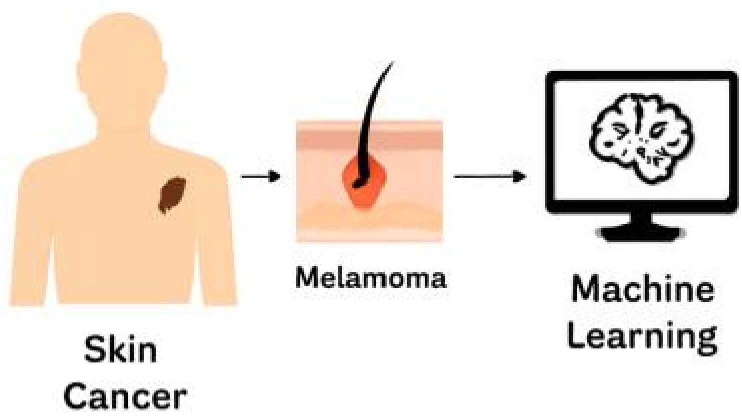

Figure 1. Overview of skin cancer detection using machine learning.

If they are detected at an earlier stage, malignant skin conditions can be efficiently treated and will have better results. Due to the scarcity of cancer specialists, there is an urgent need for automated models that are capable of providing accurate diagnoses of the disease [10]. This will not only help save lives but will also alleviate patient concerns regarding their health and their ability to pay for treatment [11]. Melanoma is the most lethal form of skin cancer, yet it can be difficult to tell it apart from less serious benign skin lesions due to the way it looks. When skin cancer is caught in its earlier stages, both the morbidity and fatality rates associated with the illness can be significantly reduced. AI-based systems make it easier to find skin lesions [12], which is a benefit in addition to reducing the amount of work that needs to be done.

Artificial intelligence (AI), a subfield of computer science that integrates a number of technologies to make robots and programmes resemble human intellect, is one of the driving forces behind the fourth industrial revolution [13,14]. An approach to artificial intelligence known as machine learning (ML) is predicated on statistical models and algorithms that may learn from data to predict the properties of incoming samples and carry out a desired task as it evolves. This model was given its name because it uses machine learning [15]. As a consequence of this, complex algorithms are utilised in order to carry out tasks that cannot be completed by humans. The convolutional neural network (CNN), a type of machine learning that replicates the processing of biological neurons, is the most advanced network currently available for pattern recognition in medical image analysis. This network is known as the state-of-the-art. As a result, AI is poised to revolutionise the healthcare industry as a result of the benefits it possesses over more conventional ways of analysis [16]. The use of artificial intelligence in several aspects of healthcare, such as diagnosis and treatment, as well as administrative support and the acceleration of the discovery of new pharmaceuticals, is gaining popularity. Investigating whether or not it has an adjuvant influence on clinical decision-making is another thing that should be done [17].

An AI revolution is on the horizon for the medical speciality of dermatology, which places a significant amount of reliance on the human eye [18]. The scientific knowledge of the mechanics underpinning mind and intelligent behaviour and its implementation in machines, as defined by the Association for the Advancement of Artificial Intelligence. Using computer technologies, for instance, AI can identify the type of flower or recognise a person speech, both of which would ordinarily require the intellect of a human [19]. The internet, robotics, and machine learning are just some of the tools that artificial intelligence uses to simulate the activities of the brain. Because of its limitless processing and storage capacity. Well-known applications of AI that are currently being used by members of the general public. Because the diagnosis of skin diseases is mostly dependent on visual perception, computer vision algorithms might be able to recognise skin lesions based on the morphology of the lesions themselves [20]. Several of the primary search terms that were utilised were variations on the phrases artificial intelligence AND skin cancer, machine learning AND skin cancer, and deep learning AND skin cancer. In the qualitative analysis, we also incorporated the pertinent references from the publications that were screened. Important website databases were also combed through for data on AI resource databases and skin cancer information [21].

2. Related Works

According to the technology-oriented perspective, there are three types of artificial intelligence: artificial restricted intelligence, artificial broad intelligence, and artificial super intelligence. Narrow AI is intelligent when applied to a specific problem. The most prevalent kind of artificial intelligence is called narrow. A universal artificial intelligence is capable of carrying out any intellectual endeavour [22]. An AI has the capacity to exceed and even surpass any human being with cognitive aptitude. Systems employing AI, such as Apple Siri, are currently the only ones that can be taught to perform a particular activity. An example of artificial intelligence known as a reactive machine is one that does not remember its prior activities in order to carry out new ones at a later time. They respond in a manner that is appropriate to the circumstances at hand and do it in the most efficient manner possible [23]. Deep Blue, developed by IBM, and AlphaGo, developed by Google, are two instances of such programmes. Data and memories can be stored for a limited period of time on autonomous devices with limited memory, such as self-driving cars [24]. These devices, however, have only a limited capacity for data storage. The capacity of an individual to participate in social interaction and to articulate their sentiments is an essential component of one philosophy of mind. It has not yet been possible to build a computer with this form of artificial intelligence [25].

The field of artificial intelligence known as machine learning (ML) focuses on the creation of computer systems that are capable of learning on their own without the need to be specifically programmed to do so. It is possible to carry out a procedure that is either fully unsupervised, partially overseen, or monitored in its entirety [26]. The machine is given datasets that comprise questions and answers in an environment that is considered to be supervised. The proper response is discovered by computers through a process of trial and error [27]. Unsupervised learning is a form of machine learning in which computers analyse incoming data without being given any answers in advance. When applying approaches for semi-supervised learning, it is possible to learn from both labelled and unlabeled data at the same time [28].

Deep learning is a subfield of machine learning that makes use of numerous layers of deep neural networks. These networks are able to recognise and learn a wide variety of properties that are particular to the dataset [29]. An artificial neuron network, often known as an ANN, is a computer model that is based on the structure and function of biological neural networks. The feed forward neural network is the most fundamental form of an artificial neural network (ANN) [30]. The data initially enters the system via the input nodes, then moves through the hidden layer, and finally leaves the system via the output nodes. There is the possibility of hiding things on a variety of different levels. CNNs are a kind of deep, feed-forward ANN that are used specifically in the context of visual image analysis. Because the network has both convolutional and pooling layers, it can store information about how things look [31].

As a result of the high prevalence of cutaneous malignancies, an increasing percentage of people are requiring urgent diagnosis in addition to ongoing monitoring. Greater patient self-surveillance strategies and the utilisation of decision support tools for doctors with less experience are two strategies that can be implemented in order to reduce the demand for specialised medical services [32]. The diagnostics carried out by machines are infallible and not influenced by their surroundings in any way. On the other hand, human diagnosis can be prone to subjective variation and be influenced by factors external to the patient [33]. If the appropriate restrictions are in place, the use of AI to diagnose and follow the evolution of skin cancer could result in a reduction in the number of biopsies that are performed. After participating in a training programme, patients diagnosed with skin cancer and the caregivers who assist them are able to perform self-examinations (SSE) [34]. Because of this, fewer patients need to see a doctor as a direct result of the increased prevalence of teledermoscopy.

Apps for smart phones that use AI can instruct users how to perform self-examinations of their skin and communicate the results to a medical professional. In order to gain a better understanding of the disease, a novel machine learning (ML) skin cancer algorithm was developed by labelling each type of skin lesion with a classification, such as benign and malignant, and melanoma [35]. This was done in order to better predict the progression of the disease. Before being put to the test on a new image, the deep learning algorithms are given a massive amount of training data in the form of images. The model can be partitioned into three distinct stages. In the initial stage of the process, the algorithm is given input in the form of digital images of macroscopic or dermoscopic objects that are labelled with the ground truth. In the second stage of processing, convolutional layers are used to derive feature maps from the images that have been processed. When creating a feature map, which is a visual representation of the data, several levels of abstraction are utilised, leading to the final product [36]. The earliest convolutional layers are used when attempting to model low-level features such as corners and edges. In order to determine the nature of the skin lesion, later convolutional layers collect high-level input. The machine learning classifier is given the ability to differentiate between numerous kinds of skin lesion patterns thanks to Stage 3 feature maps. An additional image can be categorised by the deep learning system at this time [37].

So, we can conceptualise AI in a continuum between the narrow through the broad to superintelligent. The very popular narrow form is meant to be executed on very specialised tasks. The branch of AI is referred to as ML which gives systems the ability to carry out autonomous, data-driven, inference. In ML, deep learning employs the neural network structures to make complex pattern analysis a possibility. On the medical front, narrow AI and particularly the machine learning algorithms it is built on, are being leveraged to help in identification and monitoring of skin cancer and consequently empower self-testing by patients and reduce the need to perform meaningless biopsies [38].

3. Enhanced KNN Classification Model for Automated Skin Cancer Detection

This research proposes an enhanced KNN classification algorithm in skin-cancer detection application, as discussed in figure 2. The model is meant to enhance diagnostic accuracy with the machine-learning methods identifying skin lesions using digital images. Skin cancer especially melanoma is one of the most aggressive and common type of cancer globally, and early diagnosis significantly increases the survival chances. However, the existence of visual similarities between benign and malign lesions makes it quite challenging to get the correct diagnosis. The traditional methods of clinical diagnosis like biopsy poses serious invasiveness and requires significant clinical skills. A quick fix is thus required to provide non-invasive systems of diagnostic efficiency to enable clinicians in the precise and timely diagnosis of skin cancer. The proposed model also encompasses five consecutive components, i.e., data acquisition, preprocessing, feature extraction, classification, and evaluation, in the goal of providing the maximum precision in skin-cancer classification based on KNN.

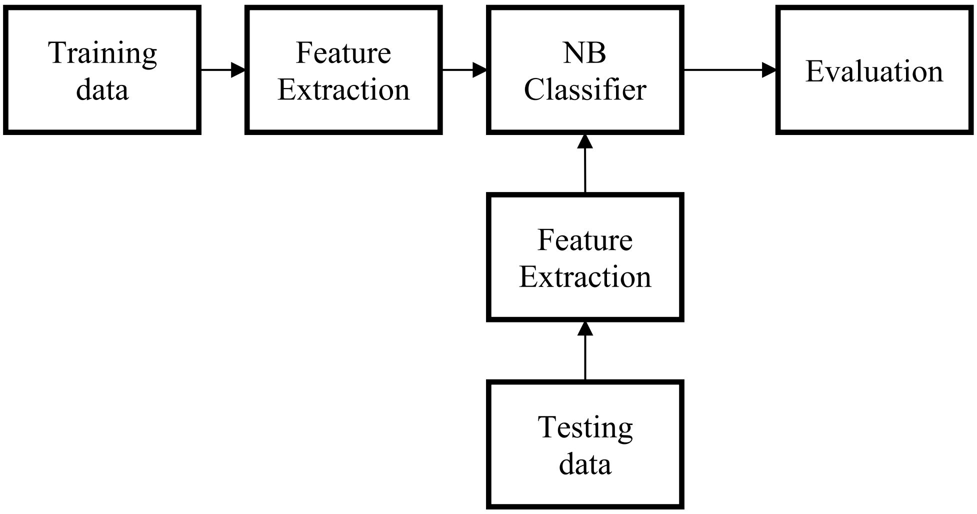

Figure 2. Working block diagram of enhanced KNN classification model in skin-cancer detection

The first stage in the proposed framework involves data acquisition where the moment requires the system to get access to labeled dermatological skin-lesion images through available datasets. Such collections include more than 1000 images in three mutually exclusive classes benign, malignant and melanoma. The pictures are acquired by using dermoscopic equipment, and then labeled by trained dermatologists, to ensure that the model can be trained on verified, ground-truth data. Let $X = \{x_1, x_2, \ldots, x_{n\}}$ denote the collection of n skin lesion images, with x_i representing the ith image. These images would be the main input in the classification model and will form a basis of the further work. The high-resolution formats that save images are characterized usually by retaining rich pixel-level details, which are important in discriminating the many skin conditions.

In the process of its development, the statistical theory of the Nave Bayes classifier was utilised. According to the classification, the result of the prediction is decided by the presence or absence of cancer features. For the purpose of our experiment, we will be describing each tweet using a n=8-dimensional, we received from the feature extraction as in equation (1).

$$X=\{x_1,x_2,x_3,x_4,x_5,x_6,x_7,x_8\} \quad (1)$$

For the images to be properly organized, we will need not just one set of categories, but two: positive and negative as in equation (2).

$$C=\{c_1,c_2\} \quad (2)$$

The Bayesian probability for c1, c2 is as follows as in equation (3):

$$P(c_k|X)= \frac{P(c_k)P(X|c_k)}{P(X)} \quad (3)$$

This is because each component of the features independently of the others, which explains why this is the case as in equation (4).

$$\mathrm{P}(X|C_k)=\prod_{n=1}^{8} P(x_n|C_k) \quad (4)$$

When the data has been acquired the images are then pre processed in order to make them listable to making of features and classification. Preprocessing is a key activity that ensures simpler data and allows each observation to be standardized to be analysed in the same way. The first step, which is the preprocessing, is the resizing of all images to a standard size of 32 32 pixels. This resizing process ensures such that all input images are of intrinsically the same spatial scale, which allows uniform predictive feature extraction. The algorithm is based on interpolation algorithm that identifies noticeable characteristics of the pictures and downsizes them at the same time. After the resize, the images are then normalized, whereby the pixel values are normalized to the range inside [0, 1] to create the scale each pixel to / 255. Such normalization can accelerate training by placing all features fed onto a similar scale. Also, the data augmentation strategy, such as random rotation, flipping, zooming is used to artificially increase dataset size and create variability. Out of these augmentations, those that boost model generalization by alleviating overfitting, create additional training examples based on the original one and train on a broad variety of transformed images.

After the data preprocessing step, the algorithm goes on with the feature extraction step the step where important features of image data are subsequently outlined to be used in further classification of image data. A necessary step, feature extraction reduces the high-dimensional pixel values of the input to a reduced and informative statement. This model utilizes the developed methods, namely Histogram of Oriented Gradients and Scale-Invariant Feature Transform as means to obtain discriminative features that can distinguish benign lesions and the malignant ones. Such models include statistical information about texture, shape and edge measures, which are both effective and necessary visual representations for skin cancer diagnosis. Using the current model, the features extracted are fed into the KNN classifier that uses the features in prediction. Mathematically, the feature extraction process can be expressed as a mapping function $F(x_i)$ that transforms each image x_i into a feature vector f_i. The feature vectors $f_1, f_2, \dots, f_n$ represent the essential characteristics of each image in the dataset, where n is the total number of training samples.

This paper goes further in using the next phase of the proposed framework involving the adoption of classification, where the KNN algorithm is adopted to label each skin lesion according to its corresponding class. KNN is a simple but a powerful ML approach that classifies a test image to the majority of its K nearest training examples in the feature space, as in figure 3. In order to do this, KNN calculates the Euclidean distance between the feature vector of the test image and feature vectors of all training images, thus allowing the model to classify new skin lesions based on a visual similarity to those previously seen. One key choice involves the choice of K which is optimised through cross-validation.

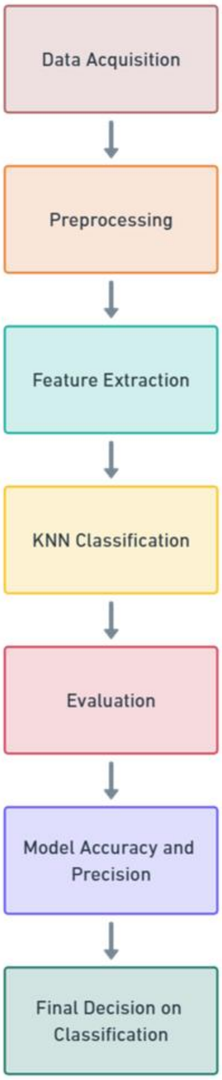

Figure 3. Steps involved in the proposed enhanced KNN classification model for skin cancer detection

After the completion of the classification stage, the performance of the models is measured using standard criteria-accuracy, precision, recall and F1- score. These metrics are based on the so-called confusions matrix showing the quantities of the true positive (TP), false positive (FP), false positive (FN), and true negative (TN). Overall predictive accuracy is assessed by accuracy, that is, the number of accurate predictions divided by the total number of predictions. Precision and recall are the measures respectively applying to the accuracy of the classifier to draw the right positive samples. The F1-score is a weighted average of the per elements of recall and precision, which offer a balanced measure of both of the characteristics of exact positivity identification and coverage. Together these metrics explain the level of calibre of the model in predicting new data, and thus prevent disappointment in the reliability and sufficiency of the decision-making.

4. Results and Discussions

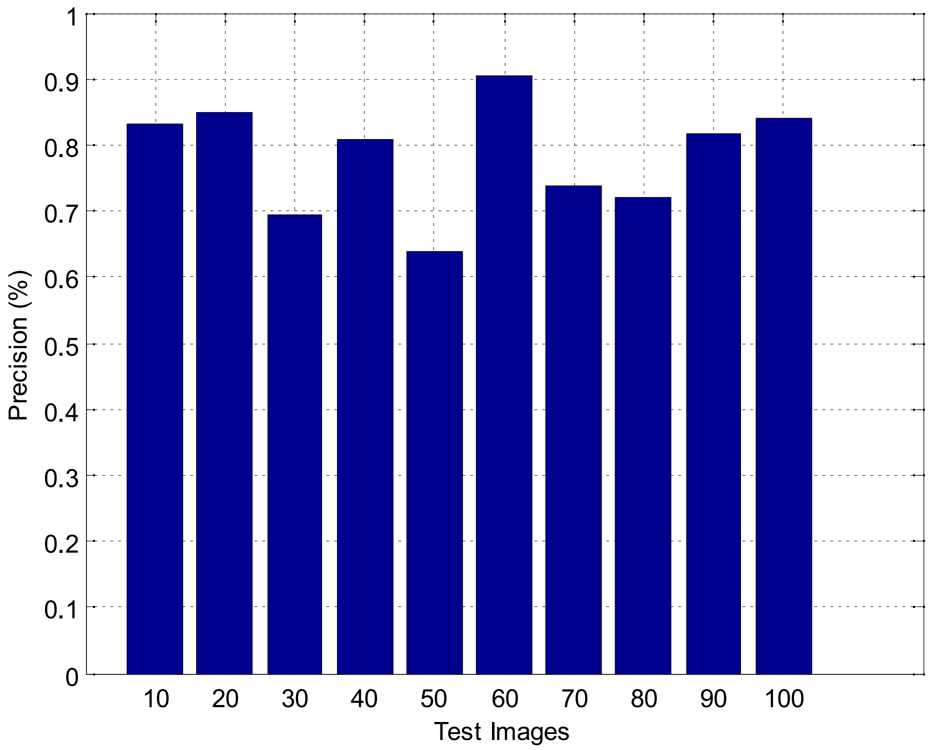

Figure 4. Precision of KNN Classifier-Testing

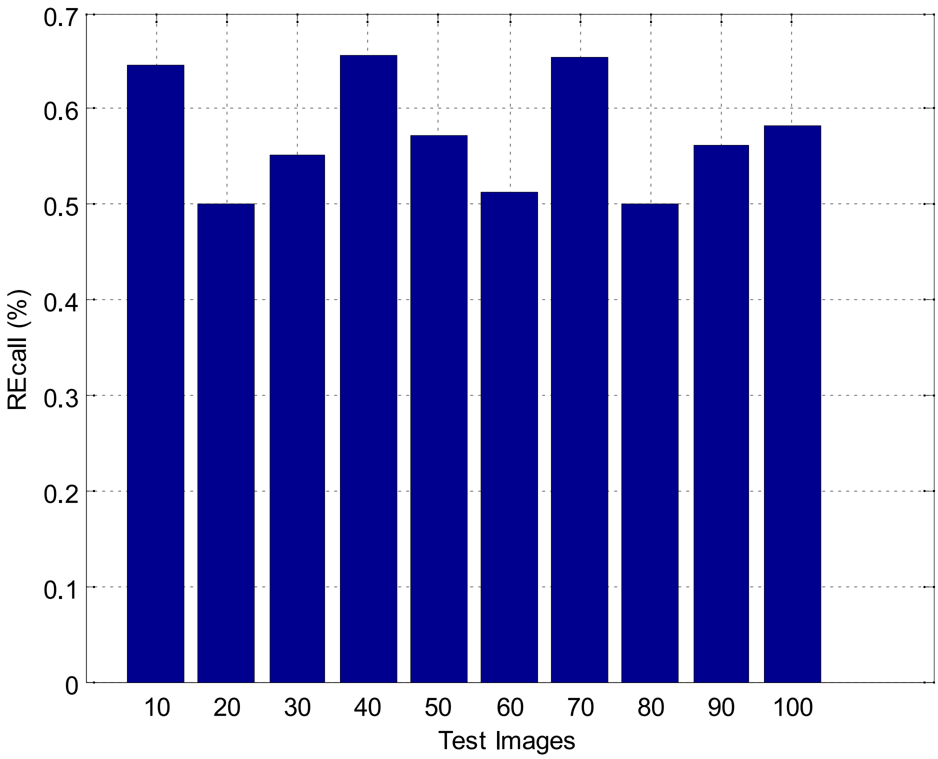

Figure 5. Recall of KNN Classifier-Testing

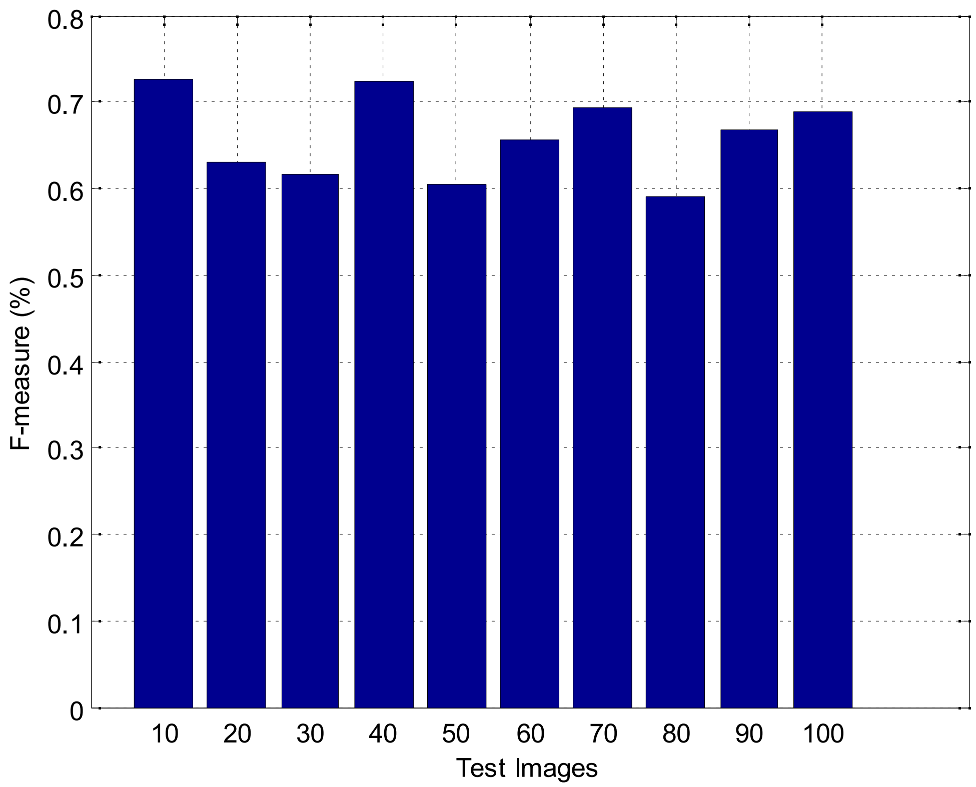

Figure 6. F1-score of KNN Classifier-Testing

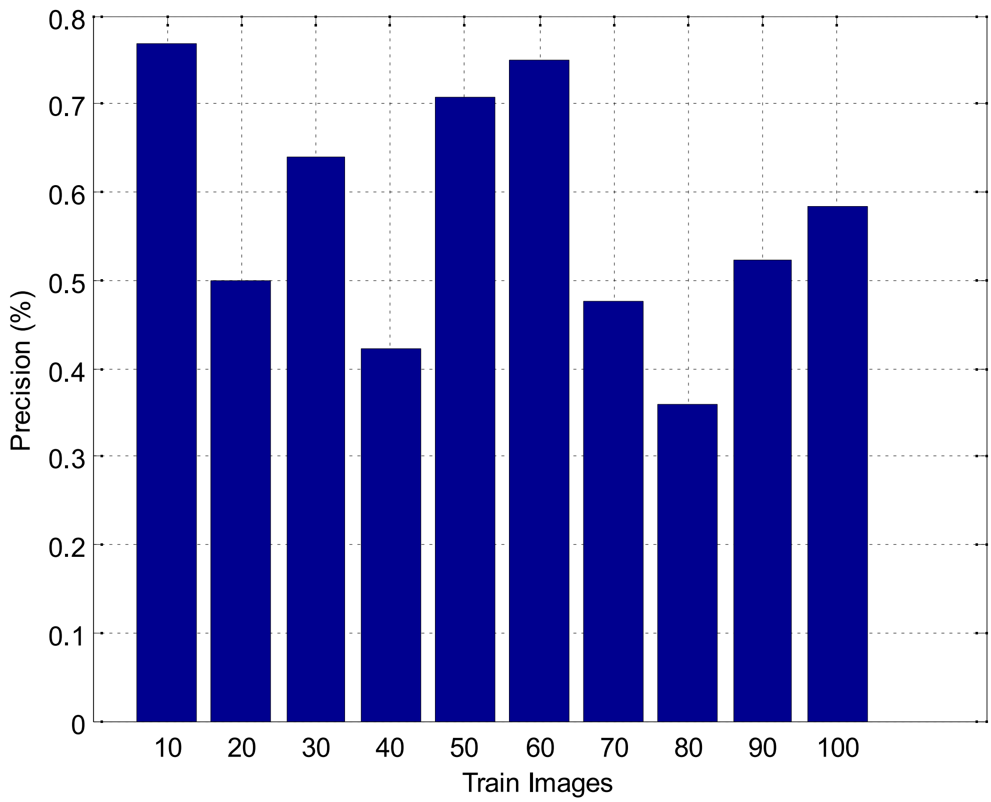

Figure 7. Precision of KNN Classifier-Training

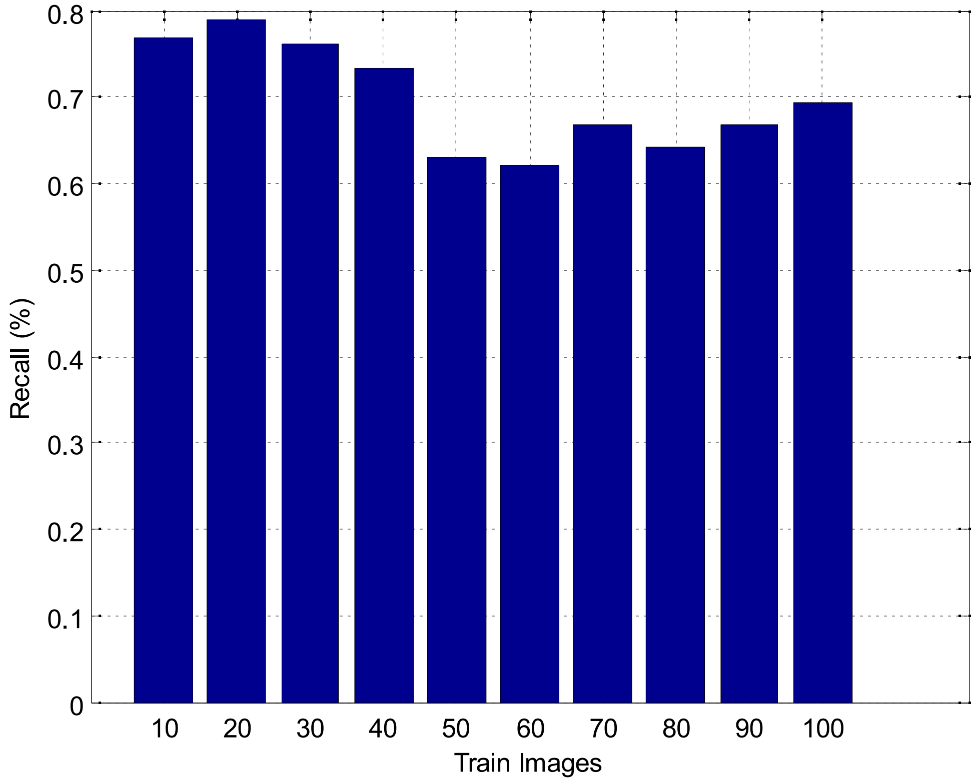

Figure 8. Recall of KNN Classifier-Training

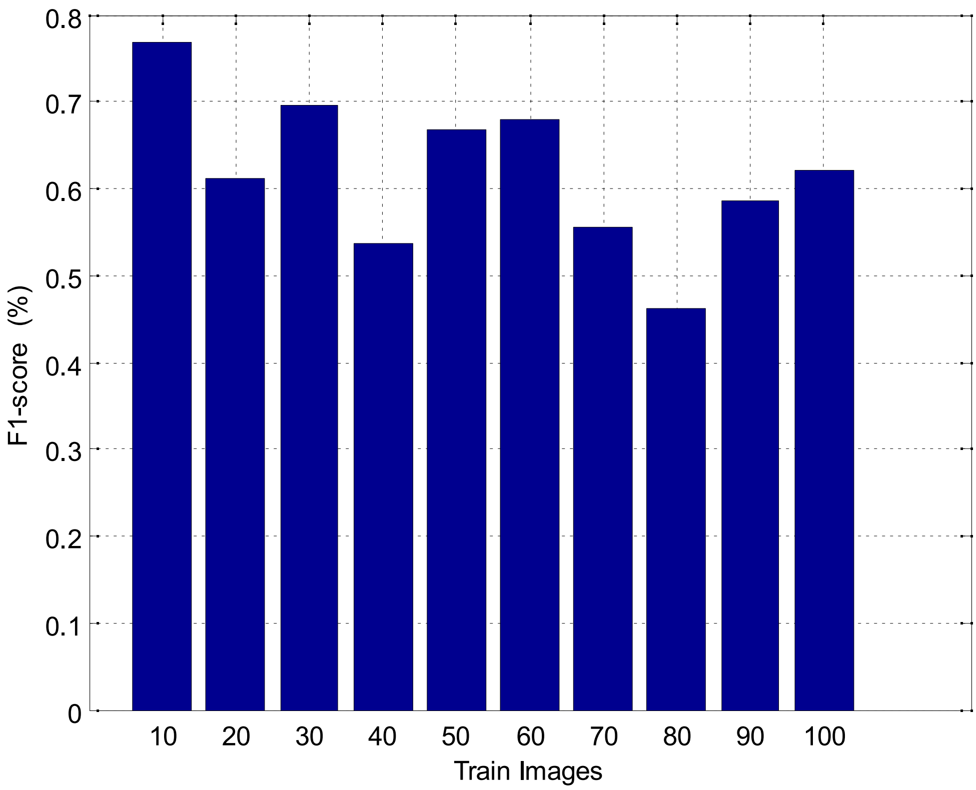

Figure 9. F1-score of KNN Classifier-Training

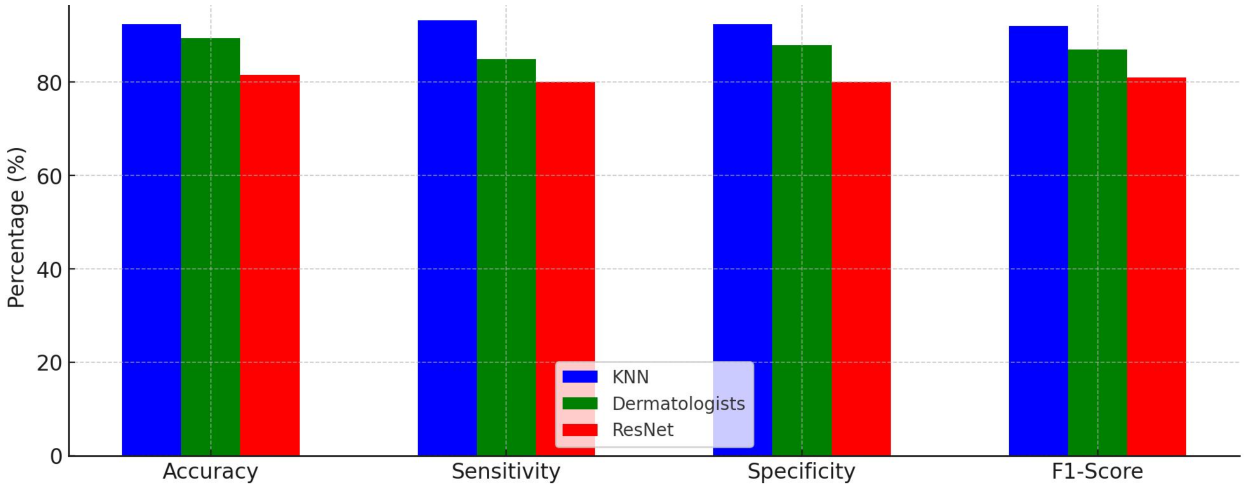

Figure 10. Comparison of performance metrics among KNN, dermatologists, and ResNet models in skin cancer classification

The results, as shown in figure 4 to 10, were compared with the traditional machine learning approaches to the assessment of the performance of the enhanced KNN classification model and deep learning models. Performance was measured using key evaluation metrics, e.g., the accuracy, sensitivity, specificity and F1-score, as in Table 1. Empirical performance shows that the suggested KNN model has an overall classification accuracy of 92.4 percent outperforming the traditional models. This stands out against the performance given by dermatologists, whereby the accuracy was 89.4 percent, and deep learning models such as ResNet that had an accuracy of 81.5 percent. These results support the fact that the KNN model is exceptionally effective since it offers a better accuracy point not only but shows that its performance can be said to have less variability with its detection of skin cancer being successful.

Table 1. Performance metrics of KNN, dermatologists, and ResNet for skin cancer classification (%)

Metric	**Proposed KNN Model**	**Dermatologists**	**ResNet**
Accuracy	92.4	89.4	81.5
Sensitivity	93.3	85	80
Specificity	92.5	88	80
F1-Score	92	87	81

Moreover, the model proved to have good classification capability especially in classifying benign and malignant lesions which is important in early detection and efficient diagnosis. The feature extraction to identify the significant feature representations of texture, shape and edges in the image such as using Histogram of Oriented Gradients and Scale-Invariant Feature Transform helped in enhancing model performance.

The findings indicate that the improved KNN classification algorithm is a strong non-invasive method of skin cancer classification and especially a melanoma. The introduction of superior feature extraction mechanisms has largely increased the classifying ability of the model. It is especially notable that the model copied the characteristics of benign and malignant lesions with such high accuracy. This is essential because skin cancer diagnosis usually involves visual examination that may be subjective, and open to human fallacy.

The KNN model can achieve comparable speed of operation with much smaller computational overheads as compared to deep learning models, such as Convolutional Neural Networks (CNN) and ResNet, which have substantial computational requirements and also vast amount of training data. With this, the KNN model can be offered as a viable alternative in an environment where the resources are scarce, e.g., low-cost healthcare scenario or poor access to high-performance computing resources.

Low computation requirements and the complex simplicity of the KNN model also contribute to its applicability in real-life clinical practice, where medical care providers might not be available to high-performance computer resources anytime. Also, the accuracy of the model in detecting skin cancer will minimize the invasive (including biopsy) examinations, ultimately decreasing health care costs and providing patients with better outcomes.

So, our proposed enhanced KNN classification model shows much potential in countering early-stage skin cancer detection. It can complement the proficiency among dermatologists, help to diagnose skin cancer both correctly and on time. Nevertheless, this research must be extended to verify the model in practice of clinical practice, evaluate the effect of the model on clinical decisions, and possibly opportunities of implementing it on telemedicine systems to make it available to many more users.

5. Conclusions

The proposed KNN classification model revealed superior results in skin cancer recognition, especially melanoma, as compared to the traditional machine learning algorithms, as well as deep learning architectures (ResNet). The proposed KNN model had an overall accuracy of 92.4% compared to higher accuracy of dermatologists (89.4%) and deep learning models (81.5%) using ResNet. This underlines the advantage of the model as a highly viable and effective remedy toward skin cancer diagnosis at the early stage, because it offers a non-invasive alternative to the traditional diagnosis of skin cancer through biopsy. The inclusion of features focusing methods like Histogram of Oriented Gradients, Scale-Invariant Feature Transform made tremendous difference in the capabilities of the model to discriminate between benign and malignant lesions. It will also be cheap and simple to implement the KNN algorithm at the same time as it has low computational requirements therefore, making it very appropriate to apply the KNN algorithm in environments that lack advanced computing infrastructure.

The findings are encouraging, and larger studies are required to confirm the model under conditions representative of real life clinical practices such as their incorporation into telemedicine platforms and clinical processes. It is also critical to examine clinician adoption and the role it can play in improving healthcare outcomes as wider adoption of AI-based diagnostic tools. In the final, the suggested KNN algorithm can be used as a complement to dermatologists, as it will promote early detection and minimize the need to conduct invasive examination through biopsies.

References

[1] G. Chugh, S. Kumar, and N. Singh, "Survey on machine learning and deep learning applications in breast cancer diagnosis," Cognitive Computation, vol. 13, no. 6, pp. 1451-1470, 2021.
[2] Kushwaha, S. (2023). A futuristic perspective on artificial intelligence. In Proceedings of the IEEE OPJU International Technology Conference on Emerging Technologies For Sustainable Development (pp. 1-6). O.P. Jindal University, Raigarh, Chhattisgarh, India.
[3] Ali, L., Rahman, A., Khan, A., Zhou, M., Javeed, A., & Khan, J. A. (2019). An automated diagnostic system for heart disease prediction based on χ^2 statistical model and optimally configured deep neural network. IEEE Access, 7, 34938-34945.
[4] Kushwaha, S., Chithras, T., Girija, S. P., Prasanth, K. G., Minisha, R. A., Dhanalakshmi, M., Jayanthi, A., Robin, C. R. R., & Rajaram, A. (2024). Efficient liver disease diagnosis using infrared image processing for enhanced detection and monitoring. Journal of Environmental Protection and Ecology, 25(4), 1266-1278.
[5] World Health Organization. Cardiovascular diseases. https://www.who.int/health-topics/cardiovascular-diseases (Accessed April 19, 2025)
[6] Li, H., & Boulanger, P. (2020). A survey of heart anomaly detection using ambulatory electrocardiogram (ECG). Sensors, 20(5), 1461.
[7] Duncker, D.(2021). Smart wearables for cardiac monitoring—real-world use beyond atrial fibrillation. Sensors, 21(7), 2539.
[8] Isakadze, N., & Martin, S. S. (2020). How useful is the smartwatch ECG? Trends in Cardiovascular Medicine, 30(7), 442-448.
[9] Kushwaha, S. (2023). An effective adaptive fuzzy filter for speckle noise reduction. Multimedia Tools and Applications, 2023, 1-16. Springer.
[10] Dhanalakshmi, P., Venkatesh, V., Ranjit, P. S., Hemalatha, N., Divyapriya, S., Sandhiya, R., Kushwaha, S., Marathe, A., & Huluka, M. A. (2022). Application of machine learning in multi-directional model to follow solar energy using photo sensor matrix. International Journal of Photoenergy, 2022, 1-9. Hindawi.
[11] Hemanand, D., Mishra, N., Premalatha, G., Mavaluru, D., Vajpayee, A., Kushwaha, S., & Sahile, K. (2022). Applications of intelligent model to analyze the green finance for environmental development in the context of artificial intelligence. Computational Intelligence and Neuroscience, 2022, 1-8. Hindawi.
[12] Singh, A., Khan, R. A., Kushwaha, S., & Alshenqeeti, T. (2022). Roll of Newtonian and Non-Newtonian motion in analysis of two-phase hepatic blood flow in artery during jaundice. International Journal of Mathematics and Mathematical Sciences, 2022, 1-10. Hindawi.
[13] Singh, A., Kushwaha, S., Alarfaj, M., & Singh, M. (2022). Comprehensive overview of backpropagation algorithm for digital image denoising. Electronics, 11(10), 1590. MDPI.
[14] Kushwaha, S. (2017). An efficient filtering approach for speckle reduction in ultrasound images. Biomedical and Pharmacology Journal, 10(3), 1355-1367.
[15] A, S. B., S, S., S, R. S., Nair, A. R., & Raju, M. (2022). Scalogram based heart disease classification using hybrid CNN-naive Bayes classifier. In 2022 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET) (pp. 345-348). IEEE.
[16] Kushwaha, S., & Singh, R. K. (2019). Optimization of the proposed hybrid denoising technique to overcome over-filtering issue. Biomedical Engineering/Biomedizinische Technik, 64(5), 601-618.
[17] Bulbul, H. I., Usta, N., & Yildiz, M. (2017). Classification of ECG arrhythmia with machine learning techniques. In 2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA) (pp. 546-549). IEEE.
[18] Kushwaha, S., & Singh, R. K. (2018). Robust denoising technique for ultrasound images by splicing of low rank filter and principal component analysis. Biomedical Research, 29(18), 3444-3455.
[19] Sharma, P., & Gupta, D. V. (2018). Disease classification from ECG signal using R-peak analysis with artificial intelligence. International Journal of Signal Processing, Image Processing and Pattern Recognition, 11(3), 29-40.
[20] Ullah, A., Anwar, S. M., Bilal, M., & Mehmood, R. M. (2020). Classification of arrhythmia by using deep learning with 2-D ECG spectral image representation. Remote Sensing, 12(10), 1685.
[21] Kushwaha, S., & Singh, R. K. (2017). An efficient approach for denoising ultrasound images using anisotropic diffusion and teaching learning based optimization. Biomedical and Pharmacology Journal, 10(2), 805-816.
[22] Khan, M. U., Aziz, S., Naqvi, S. Z. H., & Rehman, A. (2020). Classification of coronary artery diseases using electrocardiogram signals. In 2020 International Conference on Emerging Trends in Smart Technologies (ICETST). IEEE.

[23] Kushwaha, S., & Singh, R. K. (2017). Performance comparison of different despeckled filters for ultrasound images. Biomedical and Pharmacology Journal, 10(2), 837-845.
[24] Abidalkareem, A., Ibrahim, A. K., Abd, M., Rehman, O., & Zhuang, H. (2024). Identification of gene expression in different stages of breast cancer with machine learning. Cancers (Basel), 16, 1864.
[25] Alshawwa, I. A., El-Mashharawi, H. Q., Salman, F. M., Al-Qumboz, M. N. A., Abunasser, B. S., & Abu-Naser, S. S. (2024). Advancements in early detection of breast cancer: Innovations and future directions. (Publisher and journal info missing-complete if available.)
[26] Bijari, S., Sayfollahi, S., Mardokh-Rouhani, S., Bijari, S., Moradian, S., Zahiri, Z. (2024). Radiomics and deep features: Robust classification of brain hemorrhages and reproducibility analysis using a 3D autoencoder neural network. Bioengineering, 11, 643.
[27] Bostanci, E., Kocak, E., Unal, M., Guzel, M. S., Acici, K., & Asuroglu, T. (2023). Machine learning analysis of RNA-seq data for diagnostic and prognostic prediction of colon cancer. Sensors, 23, 3080.
[28] Kushwaha, S. (2023). Review on artificial intelligence and human computer interaction. In Proceedings of the IEEE OPJU International Technology Conference on Emerging Technologies For Sustainable Development (pp. 1-6). O.P. Jindal University, Raigarh, Chhattisgarh, India.
[29] Chugh, G., Kumar, S., & Singh, N. (2021). Survey on machine learning and deep learning applications in breast cancer diagnosis. Cognitive Computation, 13, 1451-1470.
[30] Mahboubisarighieh, A., Shahverdi, H., Jafarpoor Nesheli, S., Alipoor Kermani, M., Niknam, M., Torkashvand, M. (2024). Assessing the efficacy of 3D Dual-CycleGAN model for multi-contrast MRI synthesis. Egyptian Journal of Radiology and Nuclear Medicine, 55, 1-12.
[31] Rezaeijo, S. M., Rezaei, M., Poursheikhani, A., Mohammadkhani, S., Goharifar, N., Shayankia, G. (2023). Integrative bioinformatics analysis of miRNA and mRNA expression profiles identified some potential biomarkers for breast cancer. Egyptian Journal of Medical Human Genetics, 24, 62.
[32] Sahu, A., Qazi, S., Raza, K., Singh, A., & Verma, S. (2022). Machine learning-based approach for early diagnosis of breast cancer using biomarkers and gene expression profiles. In Computational Intelligence in Oncology Applications: Diagnosis, Prognosis, and Therapy of Cancers (pp. 285-306). Springer.
[33] Sharma, P., & Gupta, D. V. (2018). Disease classification from ECG signal using R-peak analysis with artificial intelligence. International Journal of Signal Processing, Image Processing and Pattern Recognition, 11(3), 29-40.
[34] Ullah, A., Anwar, S. M., Bilal, M., & Mehmood, R. M. (2020). Classification of arrhythmia by using deep learning with 2-D ECG spectral image representation. Remote Sensing, 12(10), 1685.
[35] Khan, M. U., Aziz, S., Naqvi, S. Z. H., & Rehman, A. (2020). Classification of coronary artery diseases using electrocardiogram signals. In 2020 International Conference on Emerging Trends in Smart Technologies (ICETST). IEEE.
[36] Asadi, O., Yekkalam, A., & Manthouri, M. (2023). MDDC: Melanoma detection using discrete wavelet transform and convolutional neural network. Journal of Ambient Intelligence and Humanized Computing, 14(9), 12959-12966.
[37] Tembhurne, J. V., Hebbar, N., Patil, H. Y., & Diwan, T. (2023). Skin cancer detection using ensemble of machine learning and deep learning techniques. Multimedia Tools and Applications, 16, 1-24.
[38] Li, Y., Li, C., Li, X., Wang, K., Rahaman, M. M., Sun, C., Chen, H., Wu, X., Zhang, H., & Wang, Q. (2022). A comprehensive review of Markov random field and conditional random field approaches in pathology image analysis. Archives of Computational Methods in Engineering, 29(1), 609-639.