Abstract
The skin’s fundamental function in human body as a whole-body covering is crucial. Only if it is discovered while it is in its early stages can skin cancer be cured. Skin function plays a big part in the body's overall system and will be significantly impacted by even the slightest modification. The goal of this work was to develop an effective Machine Learning (ML) based technique for identification of skin cancer using patient information. To diagnose skin cancer with lesions image, this research introduces a novel Augmented May Fly optimized with K-Nearest Neighbors (AMFO-KNN) technique. Here, the AMFO approach is used to improve the classification efficiency of KNN. Utilizing the PAD-UFES-20 and Fitzpatrick17k datasets, the efficiency of suggested method is examined. The noisy data are removed from the raw data samples using Adaptive Median Filter (AMF). The properties are taken out of segmented data using Kernel Principal Component Analysis (KPCA). The performance metrics of research show that recommended methodology performs better than traditional approaches in terms of accuracy, precision, f1-score, and recall measures. The encouraging results demonstrate the effectiveness of suggested strategy and show that including the patient’s information with lesions image may improve the performance of skin cancer diagnosis.

Keywords: SCD, metadata, patients, AMFO-KNN

1. Introduction

The challenge for dermatologists is produced from melanocyte cells, which provide a problem in the proper diagnosis of benign vs malignant lesions. Comparing malignant keratinocyte carcinoma to benign keratosis presents the same difficulties (Kousis et al 2022). Furthermore, it is difficult to distinguish between inflammatory non-neoplastic skin conditions such as dermatitis and eczema from malignant cutaneous lymphomas. The difference between benign dermal lesions (such as dermatofibroma and vascular lesions and malignant dermal lesions (like Kaposi sarcoma) is also not always easy to discern. The gold standard of diagnosis is based on biopsy and histological analysis since the visual inspection is prone to inaccuracies. The incidence of all skin-related malignancies will be divided into eight groups, which will account for 97% of the total (Malo et al 2022). Additionally, a link has been shown between the kind of lesion and the anatomical location on the body. The results prompted us to examine the effects of age, gender, and anatomical location being input into the automated model for skin cancer diagnosis (Kumar et al 2021).

Malignant lesions and benign moles often resemble one another rather closely, and both have tiny diameters that make it difficult to get good photographs with ordinary cameras (Zakhem et al 2021). For instance, because melanoma and nevus are both melanotic kinds, the categorization challenge between them is significantly greater. Additionally, the majority of patients only see their dermatologist on occasion, which results in a fatally late diagnosis (Omeroglu et al 2023). Therefore, it is necessary to provide a simple alternative for certain situations. Smartphones are the kind of digital technologies that are often the most accessible to people. With a smartphone’s photography capabilities, dermatologists, general practitioners, and patients may be able to communicate naturally about changes in skin lesions that may be concerning. (Kawahara et al 2018).

The pigment-containing cells known as melanocytes often produce the malignant melanoma type of skin cancer. Melanoma accounts for around 75% of fatalities from skin cancer and is common in non-Hispanic white men and girls (Malik and Dixit 2022). The framework is based on identifying benign or cancerous tissue using images taken with a dermatoscopistic instrument. Signal and image processing use a sort of neural network called a Convolutional Neural Network (CNN). The recommender system also uses convolutional neural networks. The reason CNN was selected for image processing was its great accuracy. Four standards are in use at CNN. The main layer serves as the input layer, where dermatologists enter all of the data have gathered. When it happens, the information is dense enough to be shifted to the category that corresponds to.
the scenario, whether benign or malignant. The study proposes an autonomous method for detecting skin cancer that uses convolutional neural networks to categorise cancer photos as either malignant or benign melanoma (Wang et al 2021).

The word “cancer” initially emerged from the Greek word “kapkivoc,” which also refers to a tumor and a crab. Cancer is a word that has been used in medicine since the 1600s to describe cells that are invasive or spreading and may impact other physiological regions. Cancer metastasis is uncontrolled cell growth that starts in one part of the body and spreads to other bodily regions. Malignant and benign cancer cells are the two kinds of cancer cells. To maximize the survival percentage of cancer patients, early, accurate diagnosis is necessary (Guergueb and Akhloufi 2022). Genetic mutations that affect cells’ activity, particularly how technique grows and divides, cause the genetic condition that causes it. Additional modifications will take place when the tumor cells expand. In essence, cancer cells contain more genetic alterations, such as DNA mutations, than healthy ones. Few cancer cells can evade the immune system, although it often eliminates damaged or aberrant cells from the body. The immune system promotes the development and survival of the tumor (Das et al 2023).

(Tajjour et al 2023) suggested the hybrid model is a network structure that manages both structured (patient information and other helpful elements from various color spaces linked to light, energy, darkness, etc.) and unstructured (images) data. The research shows the suggested hybrid model's superiority over the solo model with a 2% gain in accuracy and promising behavior when compared to ensemble approaches. Additional patient data will be used in the subsequent study to create a skin cancer screening tool. Pacheco and Krohling (2021) evaluated applying deep learning models to the issue of merging images and metadata elements for the classification of skin cancer. The suggested technique was contrasted in the research with two alternative ways to combine, one using features concatenation and the other the MetaNet. Results from two distinct skin lesion datasets demonstrate that strategy performs better than existing combination methods in six out of ten cases and improves classification for all evaluated models.

Qureshi and Roos (2022) suggested the method that enhances the model's capacity to deal with sparse and unbalanced input. Using a dataset of 33,126 dermoscopic images from 2056 patients, the study illustrates the advantages of the suggested method. The chosen method compares well across all assessment measures. (Ningrum et al 2021) indicated the capacity of deep convolutional neural networks (CNN) to forecast outcomes from both simple and complex imagery. However, its execution requires a sophisticated computing infrastructure, which is impractical in rural and low-resource healthcare settings. The combination of image and patient information has promise, but further research is needed. On several publicly accessible datasets, image feature extraction and lesion classification were carried out. Bhimavarapu and Battineni (2022) suggested Support Vector Machine (SVM) and fuzzy together provided a classification accuracy and sensitivity and specificity of 100% and 99.75%, respectively. Dai et al (2019) presented an on-device inference App and presents a proof of concept using a dataset of skin cancer photos.

Combalia et al (2022) aimed to inform doctors and regulatory bodies about security and accurate real-world classification, the research simulates each diagnostic category that was contained in the training data as well as extra diagnoses not included in the training data were represented by images in the test datasets. Luu et al (2021) compared the performance of the algorithms in contrast to 18 dermatologists in a setting simulating their intended clinical use. The 32 tissue samples with Squamous Cell Carcinoma, Basal Cell Carcinoma, melanoma, and normal characteristics are used in the proposed approach, which feeds 669 data points corresponding to the 16 Mueller matrices components as predictors into a Random Forest (RF) classifier. Babu and peter (2021) suggested a reliable method for detecting skin cancer that uses the Support Vector Machine (SVM) features. The grayscale conversion and a median filter for pre-processing skin cancer photos from the International Skin Imaging Collaboration 2018 dataset. After that, the class distribution is balanced again using the image-sembling process. The preprocessed images are used to extract the features. Saba et al (2019) preferred a revolutionary automated system for recognizing and diagnosing skin lesions that are based on Deep Convolutional Neural Networks (DCNN). The following are some potential noteworthy contributions that a study on transformation based on skin cancer detection may emphasize:

- The performance of the machine learning algorithm used to diagnose skin cancer across a variety of skin lesion datasets was examined in a publication that provided an update on the subject.
- The technical difficulties of these algorithms are reviewed in the context of digital dermatology, along with chances to augment the present machine learning (ML) based image classification solutions so that physicians may utilize them to increase efficiency.

The remaining part of the study is organized into three sections: Section 2 offers recommendations for further research based on the findings and describes the research strategy and techniques used to collect and evaluate data. Before presenting the research results concisely and systematically, we go through the Discussion and results in section 3 and evaluate and describe them in light of the study aims or objectives. Section 4 provides an overview of the Study’s main elements, as well as its relevance and contributions, potential repercussions for practice or policy, and potential future study areas.

2. Materials and Methods
2.1. Data Collection

The PAD-UFES-20, the International Skin Imaging Collaboration Dermoscopic Archive, and a portion of the Fitzpatrick17k images were the three datasets utilised to train and assess the proposed system. The International Skin Imaging Collaboration Dermoscopic Archive was published for the 2019 and 2020 melanoma detection challenges. International Skin Imaging Collaboration 2019 includes photos that fall under nine distinct diagnostic categories. According to (Ahmadi Mehr and Ameri 2022), International Skin Imaging Collaboration 2020 includes photos of distinctive benign and malignant skin lesions from over 2,000 individuals, and all images are dermoscopic, biopsy-proven, and labeled as malignant or benign. Histopathology was used to confirm all malignant diagnoses; benign diagnoses were either verified by expert consensus, long-term follow-up, or histopathology. The metadata in both International Skin Imaging Collaboration databases include details on the patient’s gender, age, and anatomical location of the lesion on their bodies. The PAD-UFES-20 is made up of photographic samples of six distinct kinds of skin lesions, with each image indicating whether or not it has undergone a biopsy, which is the only way to confirm the presence of malignant lesions. Additional information included in this dataset includes the patient’s gender, age, and anatomical location of the lesion. Figure 1 shows the image difference between Malignant, benign are all included in the Fitzpatrick17k’s three-partition label for photographic images. Fitzpatrick17k did not, however, include any information. Our dataset, created from the three aforementioned databases, consists of 66735 clinical photos that reflect 16 distinct skin-disease situations. These images include 58031 dermoscopy images and 8704 photographs, respectively. To illustrate the differences between photographic and dermoscopic images for melanocytic lesions, one example image from the dataset is provided.

Figure 1 Photographic and dermoscopic images for melanocytic lesions to visualize the difference (Ahmadi Mehr and Ameri 2022).

2.2. Data pre-processing using Adaptive median filter (AMF)

A more sophisticated variation of the conventional median filter is the AMF technique. Through spatial processing, impulse noise is eliminated. The AMF classifies each pixel in the skin image with its neighboring pixels to determine whether there is noise or not. It is superior to other filters because it preserves the image’s fine features and reduces non-impulse noise. It is also quite probable that it can adjust to impulsive noise. Similar to how the mean channel reduces disorder in a image, the median channel does the same. The median channel might be different for two descriptions, as in equation 1,

$$\text{med}(n_k) = \begin{cases} n_i + 1^a = 2i + 1(\text{ODD}) \\ \frac{n_i+n_{i+1}}{2} = 2i(\text{even}) \end{cases}$$

(1)

Here $n_i$ is the $i^{th}$ the biggest observed data and $n_1; n_2; n_3... n_i$ are the observed data. Consider a situation in which there are 7 samples total in the data collection 2, 3.5, 1, 3, 1.5, and 4 and the median filter yields an output of 2.5. The signal will remain intact if the pulse is $n + 1$ or longer; if not, it will be eliminated from the series. What distinguishes the median filter from other filters is its ability to suppress pulse noise while maintaining local characteristics. This method then sends the signal it produces to the feature extraction stage.

2.3. Feature extraction by using Kernel Principal Component Analysis (KPCA)

A basis transformation known as Principal Component Analysis (PCA) is used to diagonalize an approximation of the covariance matrix of the data in equation 2,

$$D = \frac{1}{k} \sum_{i=1}^{k} v_i v_i^S$$

(2)
Principal components are the new coordinates in the tile Eigenvector basis or the orthogonal projections onto the Eigenvectors. This setting is expanded upon in this study to a nonlinear setting of the following kind. If equation 3 were to first nonlinearly map the data into a feature space. 

\[ \Phi: Q^M \rightarrow E, v \rightarrow V \]  

(3)

We’ll demonstrate that, for certain values, we can still do PCA in E even if it has arbitrarily high dimensionality. Assume that equation 4 maps data into feature space for the time being. For the covariance matrix, do PCA. 

\[ \overline{D} = \frac{1}{k} \sum_{i=1}^{k} \Phi(v_i)\Phi(v_i)^T \]  

(4)

Principal component analysis (KPCA) is a nonlinear variation that is often used in denoising and wavelet transform applications. When the manifold is linearly buried in the observation space, the conventional PCA method seeks to decrease dimensionality. The manifold is linearized using one of the two components of KPCA, the kernel method, to meet the needs of the PCA, the other component. KPCA automatically projects data into a pairwise-specific pairwise formula between the mapped data in the feature set using feature mapping. This pairwise formula is computed by the kernel. Finding a suitable kernel that takes the geometry of the input space into account and linearizes the surface in the feature space is challenging. A poor projection that does not meet these requirements would render KPCA's nonlinear dimensionality reduction useless.

2.4. Augmented May Fly optimized with K-Nearest Neighbors (AMFO-KNN)

The specific combination of Augmented May Fly optimized with k-nearest neighbors (KNN) in the field of skin cancer detection based on patients’ information may not be widely accepted. When the two components (May Fly optimization and KNN) are combined, we may propose a concept where the May Fly optimization is included in the k-nearest neighbors method to improve the efficiency of cancer detection and attention optimization. The attention optimization within the integrating binary attention modules may be changed at different KNN levels as part of this integration. The effectiveness of the proposed approach would vary depending on the specific dataset, the nature of the skin cancer detection issue, and the computational resources available. May Fly and k-nearest neighbors may be combined to enhance attention optimization and the efficiency of intrusion detection systems. Based on these factors, we may investigate a potential idea: To establish the practicality and use of this precise combination in the context of skin cancer detection, more research and development would be necessary.

2.4.1. Augmented May Fly optimization

The insects’ interactions with one another, especially during mating, served as the inspiration for the mayfly algorithm. Mayflies are presumptively regarded as adults as soon as the eggs hatch. Mayflies have a lifetime, but only the fittest often survive. There is a spot for each mayfly in the search region that relates to a solution to the issue. In the traditional Mayfly method and functions are used to create new variables that ultimately lead to the local optimum. The researchers combined MA with Levy flight to improve ability to find and provide the optimal solution. The Levy flight hypothesis says that, in contrast to stochastic random search, a Levy flight-based approach for system identification rapidly converges and does not need derivative knowledge. Levy flying significantly enhances local search avoidance and local trapping of the best solution. Figure 2 depicts the flowchart for the suggested AMFO approach. The suggested mayfly optimization technique needs the following steps to work:

Step 1: There should be two groups of mayflies, one for each gender, representing the male and female populations.

Step 2: A mayfly’s positional shift serves as the initiation of its velocity. A composite interplay between people and social flying experiences determines its course. Every mayfly tends to change its course to match its current personal best position (pbest). Additionally, it changes dependent on the best position attained by every other mayfly in the swarm up to that point (gbest). Equation 5’s male mayfly population was initiated as, 

\[ O_{[m]}(j = 1,2,\ldots, MH) \]  

(5)

Step 3: Male mayfly swarms show that each mayfly’s location varies based on its experiences and those of its neighbors. The mayfly’s current location in the search space at the current time step is denoted by \( O_{[m]}^{t+1} \), and its position is altered by adding the current velocity \( O_{[m]}^{t+1} \). Equation 6 is represented by the following notation:

\[ O_{[m]}^{t+1} = O_{[m]}^{t} + O_{[m]}^{t+1} \]  

(6)

Male mayflies are categorized as equation 7 when they are seen dancing nuptially a few meters above the water,

\[ O_{[m]}^{0}w(O_{[m]}^{t+j}, O_{[m]}^{t+j}) \]  

(7)
It may be assumed that these mayflies don’t have very fast speeds since they are always moving. Equation 8 may be used to compute the speed of a male mayfly as shown below:

\[ w_{ji}^{s+1} = h * w_{ji}^s + b_1 h^{-\beta q_0} (obest_{ji} - 0_{Hnj}^s) + b_2 h^{-\beta q_0} (obest_{ji} - 0_{Hnj}^s) \]  

Equation 8

Additionally, obest, represents the best location the mayfly has ever been. The personal best position at the next time step equation 9 was computed as stated below based on the minimization issues under consideration,

\[ obest_i = \begin{cases} 0_{Hnj}^{s+1}, & \text{if } e(0_{Hnj}^{s+1}) < e(obest_i) \\ \text{is kept the same, otherwise} & \end{cases} \]  

Equation 9

The female mayflies indicate in equation 10 that each mayfly’s location changes according to its own experience. The equation for the world’s best position, gbest at time step, is given below,

\[ gbest \epsilon \{ pbest_1, pbest_2, ..., pbest_M, e(cbest) \}, = \min \{ e(pbest_1), e(pbest_2), ..., e(pbest_M) \} \]  

Equation 10

Figure 2: Flow chart of Augmented May Fly Optimization.
2.4.2. K-Nearest Neighbors

Using the KNN algorithm, skin cancer is detected. With the discovery of his method, skin cancer classification may be done while test samples and training samples are fed into databases. The closest diameter to the preparation casing is used to classify samples. The classification of the sample is then completed by its portion. By capturing the k nearby position and announcing the indication of the mainstream, the KNN classifier broadens this recommendation. It is distinct to choose k values. Choosing the value of k is often done during cross-validation, and larger values of k may help to mitigate the effects of noise levels in the pixels rate within the training data set. Here, one of the many solutions available for this issue is to choose a portion of the training data such that classification by 1-NN rules may be done utilizing values from several subsets. Using the K-Nearest Neighbors (KNN) technique, the geometrical feature extraction result values were categorized. The researchers manually entered the datasets into the same system and kept track of them. The diagnosis for each sample image in the collection was accurately labeled and sourced from the International Skin Imaging Collaboration repository.

3. Results

3.1. Evaluation of the performance of the AMFO-KNN model by comparing proposed and existing technique

Figures 3, 4, 5, and 6 show that the four-assessment metrics of prediction performance based on present and planned AMFO-KNN algorithms are especially clear in the macro recall metric. Although there are significant variances in F1-score, precision, accuracy, and recall, the results of predictions don't vary much.

3.1.1. Accuracy

An important parameter to evaluate the dependability and efficiency of the system is how reliably the skin cancer diagnosis employing the AMFO-KNN detects the skin cancer. It takes into account both accurately predicted positive and negative outcomes as well as accurately predicted positive and negative outcomes that were incorrect. As seen in equation 11, detection with more accuracy may detect with more precision, resulting in fewer false positives and false negatives.

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (11)
\]

The accuracy of the suggested and existing approaches is shown in Figure 3. A percentage of the total is often used to represent the accuracy level. Both the existing procedure and the suggested one have the potential for inaccurate estimates. This danger is recognized by both systems. However, the suggested method AMFO-KNN has a 48% accuracy rate compared to 18% for SVM, 24% for DCNN, and 34% for RF. The proposed approach thus has the best accuracy rate. Table 1 displays the recommended method’s accuracy.

![Figure 3](image)

**Table 1** Numerical outcomes of the accuracy of a proposed and existing method.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM (Babu and Peter 2021)</td>
<td>18</td>
</tr>
<tr>
<td>DCNN (Saba et al 2019)</td>
<td>24</td>
</tr>
<tr>
<td>RF (Luu et al 2021)</td>
<td>34</td>
</tr>
<tr>
<td>AMFO-KNN (Proposed)</td>
<td>48</td>
</tr>
</tbody>
</table>
3.1.2. Precision

The ability of a system to identify cases of skin cancer diagnosis is measured by precision, a performance metric. The proportion of correct diagnoses among all positive predictions given by the system, including both true positives and false positives, is the object of particular attention. A high accuracy value in equation 12 indicates that there are fewer false positives than false alerts, demonstrating that the system is effective in properly identifying true invasions while reducing false alarms. On the other side, a low accuracy score suggests that the system may produce a large percentage of false positives, which might cause unnecessary alerts and add to the workload.

\[
\text{precision} = \frac{TP}{TP+FP} \quad (12)
\]

The Precision of the suggested and existing approaches is shown in Figure 4. A percentage of the total is often used to represent the accuracy level. Both the existing procedure and the suggested one have the potential for inaccurate estimates. This danger is recognized by both systems. The suggested approach, AMFO-KNN, has a 45% Precision rate, compared to 20%, 26%, and 36% for SVM, DCNN, and RF, respectively. The proposed approach, therefore, has the greatest Precision rate. Table 2 displays the proposed method’s Precision.

![Figure 4 Comparison of precision.](image)

Table 2 Numerical outcomes of precision of proposed and existing method.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Precision (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM (Babu and Peter 2021)</td>
<td>20</td>
</tr>
<tr>
<td>DCNN (Saba et al 2019)</td>
<td>26</td>
</tr>
<tr>
<td>RF (Luu et al 2021)</td>
<td>36</td>
</tr>
<tr>
<td>AMFO-KNN (Proposed)</td>
<td>45</td>
</tr>
</tbody>
</table>

3.1.3. Recall

The recall is a performance metric that evaluates how effectively a system can discriminate between skin cancer diagnoses, also known as sensitivity or true positive rate. Equation 13 shows that a system with a high recall value is likely to be effective in identifying the majority of cancer diagnoses with a low occurrence of false negatives. On the other side, a low recall value suggests that the system may have a large percentage of false negatives and may miss a significant amount of real invasions.

\[
\text{Recall} = \frac{FN}{FN+TP} \quad (13)
\]

The recollection of the recommended and existing strategies is shown in Figure 5. Recall percentages are often stated as a percentage of the whole sample. Both the existing procedure and the suggested one have the potential for inaccurate estimates. This danger is recognized by both systems. This danger is recognized by both systems. However, SVM, DCNN, and RF only obtain 15%, 23%, and 32% Recall rates, respectively, but the suggested approach, AMFO-KNN, has a 47% Recall rate. The proposed approach, therefore, has the greatest Precision rate. Table 3 displays the recall for the recommended strategy.

Table 3 Numerical Outcomes of Recall of Proposed and existing methods.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Recall (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM (Babu and Peter 2021)</td>
<td>15</td>
</tr>
<tr>
<td>DCNN (Saba et al 2019)</td>
<td>23</td>
</tr>
<tr>
<td>RF (Luu et al 2021)</td>
<td>32</td>
</tr>
<tr>
<td>AMFO-KNN (Proposed)</td>
<td>47</td>
</tr>
</tbody>
</table>
3.1.4. F1-score

An achievement statistic called the F1 score combines recall and accuracy into a single factor. It provides a fair evaluation of the system’s ability to correctly identify both positive and negative situations by accounting for both false positives and false negatives. Equation 14 is trade-off between minimizing false positives and false negatives is balanced by the F1-score, which provides a detailed evaluation of the system’s performance.

$$F1 = \frac{(\text{precision}) \times (\text{recall}) \times 2}{\text{precision} + \text{recall}}$$ (14)

The F1-Score for the proposed and existing approaches is shown in Figure 6. The F1-Score levels are often reported as a percentage of the total. Both the existing procedure and the suggested one have the potential for inaccurate estimates. This danger is recognized by both systems. However, the suggested technique AMFO-KNN has a 49% F1-score rate compared to 23% for SVM, 28% for DCNN, and 36% for RF. The proposed approach, therefore, has the greatest Precision rate. Table 4 displays the F1-Score for the proposed strategy.

<table>
<thead>
<tr>
<th>Methods</th>
<th>F1-score (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM (Babu and Peter 2021)</td>
<td>23</td>
</tr>
<tr>
<td>DCNN (Saba et al 2019)</td>
<td>28</td>
</tr>
<tr>
<td>RF (Luu et al 2021)</td>
<td>36</td>
</tr>
<tr>
<td>AMFO-KNN (Proposed)</td>
<td>49</td>
</tr>
</tbody>
</table>

Figure 5 Comparison of recall.

Figure 6 Comparison of F1-score.
4. Conclusions

A brand-new AMFO-KNN technique for classifying skin lesions in photos with integrated information was presented in this study. The findings show that by integrating the patient's information as the model's input data, the suggested strategy enhanced the performance of skin cancer detection. The suggested technique was successful in classifying four significant skin disorders and was 94.5% accurate in identifying benign from malignant lesions. Larger public datasets with metadata should be developed in this area going forward to support research community efforts and improve deep learning-based automated categorization of skin lesions. Future research is required to look at how augmentation techniques such as cutout regularization affect CNN performance. Early detection is crucial if this kind of skin cancer is to be treated completely. However, it won't be able to cure it if it gets aggressive and spreads to other body parts. Therefore, early detection of skin cancer may enhance a patient's prognosis and lower the danger of the illness transmitting to patients. Future uses of this study may include incorporating this model into automated diagnostic technologies to improve the diagnostic proficiency of clinical dermatologists and oncologists. To create an effective diagnostic system for skin cancer detection, this research presented a novel KNN approach. Further, we conclude that the accuracy of the classification stage of the KNN is improved by this model's usage of the Swish activation function and depth-wise separable convolutions. The Fitzpatrick17k skin cancer dataset was then used to apply the suggested KNN algorithm, and the outcomes were compared with various cutting-edge techniques. The suggested strategy performed the best among the others, according to the results, with 48% accuracy, 45% precision, 47% recall, and 49% F1-score. It seems that employing any of the implementations we developed using machine learning has a considerable increase in accuracy based on the findings obtained in the comparison of these techniques.

Ethical considerations

Not applicable.

Declaration of interest

The authors declare no conflicts of interest.

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