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A Deep Learning Approach For Skin Cancer Image Classification And Detection Using CNN Yolov5 Algorithm

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Abstract: Skin cancer is a rapidly growing complex disease that increasing challenge to international health organization. Traditional methods for detecting skin cancer challenges are accurately identifying the type and severity of the disease through image processing techniques. To address these limitations, a novel Classification Convolutional Neural Network (CNN) with YOLOv5 algorithm is applied for precise skin image prediction. The HAM10000 dataset is used as the input source, and a Sharpening Spatial Filter (SSF) is applied as a filtering process to improve the sharpness of the images during preprocessing. For skin cancer segmentation, the Mean Shift Clustering (MSC) technique is used to identify high thickness areas in the affected region. The Optimal Region Function Neural Network (ORFNN) is then used for feature selection, removing multi-scale and non-redundant texture features from segmented images, which improves the distinction between malignant and benign lesions. CNNs are utilized for feature extraction to differentiate cancerous from benign lesions, while YOLOv5 enables proper detection and localization of skin cancer areas, ensuring accurate classification. The method categorizes skin cancer into four diseases types: Melanoma (MEL), Necrobiosis Lipoidica, Actinic Keratoses (AKIEC), and Dermatofibroma (DF). The proposed model demonstrates improved achievement with an accuracy 98.05%, precision 96%, specificity 96%, PPV 96.55%, and NPV 96.45%.

Keywords**:** Skin cancer, Optimal Region Function Neural Network (ORFNN), feature selection, Image Classification, YOLOv5.

1. INTRODUCTION

Skin cells normally grow and divide in an un-structed cell, but when they start to divide abnormally, skin cancer develops. Skin diseases has become more common in recent decades, mostly as a result of aging populations and increased exposure to environmental factors that can cause abnormal growth and the development of lumps or lesions. To calculated the accuracy of melanoma identification, deep clustering techniques have been developed for analyzing dermoscopy images. COM-Triplet loss function, facilitate adaptive learning of discriminative embeddings during training by maximizing the metric distance between cluster centers [1].

Skin lesions are broadly categorized as benign (non-cancerous) or malignant (cancerous). Vascular Lesions (VASC), Melanocytic Nevi (NV), MEL, BCC and AKIEC, and seborrheic keratosis, exhibit orderly growth patterns and do not invade surrounding tissues. Conversely, malignant lesions are characterized by uncontrolled progress that can invade nearby tissues and circulate to other portions of the body. Pre-processing techniques are critical in medical imaging to eliminate objects such as hair, Capillaries, and uneven lighting, which can obscure the features of skin lesions. Advanced image processing tools also address aging skin features, including wrinkles, stretch marks, and texture changes, ensuring clearer diagnostic images [2].

Dermoscopy, a widely used non-invasive imaging technique, captures magnified and illuminated images of the skin. This enhances the visualization of skin lesions, enabling dermatologists to detect skin cancer in its early stages and improve diagnostic accuracy. Malignant lesions often exhibit distinct color patterns, with keratin contributing yellow or orange hues and hemoglobin producing red, purple, blue, or black tone. The dataset used for analysis includes images of skin lesions from seven classes. Number of dermoscopic images of pigmented skin scratches from all major diagnostic categories, including actinic keratoses, are included in the ISIC and HAM10000 datasets [3].

Feature selection is essential for improving the performance of models used to classify skin cancer. Filter-based feature selection techniques evaluate the main attributes of the dataset, incorporating them into a feature subset to enhance model performance. Rank-based evaluation employs univariate statistical techniques to rank individual features while ignoring feature intercorrelation. In contrast, multivariate feature selection methods, which account for feature interactions and dependencies, are generally more effective for skin cancer diagnosis [4].

Convolutional neural networks (CNNs) use to classify training set, correlations between particular image patches and signature patterns are found using normal feature identifier or filters. By lowering the dimensionality of the feature space, dimensionality reduction strategies like pooling or aggregation algorithms improve computational efficiency. Generally, a CNN architecture contains of an input layer, several hidden layers (e.g. G. an output layer, as well as convolutional,

pooling, fully connected, and normalization layers. Effective image processing, segmentation, and classification are made possible by this tiered structure [5] [6].
During the segmentation process, clustering optimizes the division of image components, such as "a" and "b." Following successful segmentation, the shape feature extraction process converts the segmented image to binary. Color and shape characteristics, such as energy, homogeneity, correlation, contrast, metric, and eccentricity, are then extracted. Based on these values, the system can differentiate between six types of skin diseases: vascular lesion, pigmented benign keratosis, melanoma, nevus, basal cell carcinoma, and dermatofibroma [7].
Skin cancer, which frequently appears in sun-exposed areas of the skin, is caused by the unchecked growth of skin cells. Melanoma, Squamous Cell Carcinoma (SCC), and Basal Cell Carcinoma (BCC) are the three primary types of skin cancer. The chance of a successful course of treatment for skin cancer is greatly increased by early classification (for more information, see Section 1). However, the creation of thorough diagnostic systems is hampered by a number of issues. The main ones that have delayed the comprehensive use of deep learning techniques for skin cancer classification are data imbalances and a dearth of labeled images [8].

1.1 CONTRIBUTION OF THE WORK

The contribution of this work is the progress of classification techniques in image processing, specifically in the area of skin cancer detection. The Mean Shift clustering method is used to divide affected areas into clusters, allowing for the identification of Distinct types of skin cancer such as Melanoma (MEL), Necrobiosis Lipoidica, and Actinic Keratoses (AKIEC), as well as the severity stages of normal, benign, and malignant. This is achieved through the use of a CNN with the YOLOv5 classification method, and the Optimal Region Function Neural Network (ORFNN) is utilized for disease detection
This work is framed as follows: Section I provides an outline of skin cancer, various sickness detection and CNN classification techniques. Section II reviews previous methods that have applied different classification algorithms for skin cancer. Section III describes the proposed work, with the flow diagram and a detailed explanation of each method used in this work. Section IV discusses the types of datasets used and the total number of images used for the experiment evaluation, comparison of the outcomes. Finally, Section V concludes the skin cancer by discussing the outputs and the achieved results

2. RELATED WORK

Karthik et al. [9] suggest using a hybrid classification system combining two tracks: the Swin Transformer and the Dense Group Shuffle Non-Local Attention (DGSNLA) Network. The DGSNLA incorporates DenseNet169, Group Shuffle Depth-wise (GSDW) blocks, and an Enhanced Non-Local Attention (ENLA) block. This system was evaluated using the HAM10000 dataset. In the first track, global features are extracted from input images using the Swin Transformer, while in the second track, local features are captured through the DGSNLA network, achieving an accuracy of 94.21%.
Khan et al. [10] explored multi-class skin lesion detection and classification using tele-dermatology. This approach leverages advanced image analysis and machine learning techniques to remotely diagnose various skin conditions. Lesions are classified into classes such as benign nevi, melanoma, and other skin conditions using dermoscopic images. The method enables dermatologists to diagnose patients quickly and intervene early. For evaluation, four datasets, including the challenging HAM10000 dataset, were utilized for segmentation and classification tasks.
Gallazzi et al. [11] investigated multi label skin lesion classification using Transformer-based deep neural networks. Transformers, initially developed for natural language dealing out tasks, have demonstrated remarkable success in capturing long-range dependencies, even in image data. Their exploratory approach incorporated a relative augmentation technique, where images in the test dataset were randomly rotated during each cycle before classification. The study used a large dataset created by combining smaller datasets, achieving an accuracy of 86%.
Nie et al. [12] reviewed studies in the Web database focusing on artificial intelligence and deep learning applications in dermatology. The review emphasized deep learning frameworks, including interfaces, libraries, and tools that facilitate efficient model development. Data augmentation techniques were highlighted as a means to expand training datasets by transforming input images, thus preventing overfitting, which is common when limited training data is used.
Vachmanus et al. [13] introduced DeepMetaForge, a method for skin lesion classification using BEiT as the primary image encoder and incorporating novel skin lesion image databases. By adding a fully connected layer, the feature map size was reduced, enabling effective metadata fusion and assessment of skin conditions. This framework was applied to four publicly available dermoscopic and smartphone image datasets, achieving an average macro F1 score of 87.1%.
Bakheet et al. [14] Melanoma skin cancer identification from dermoscopic images is an automatically performed challenge. Lesion image segmentation is an important stage in any CAD system for skin cancer, since it detects skin lesion Regions of Interest (ROIs) in images. For the purpose of creating the most accurate visual representation of the preprocessed skin lesions for visual comprehension, the feature extraction method is crucial for determining the salient characteristics of the lesions. The CAD framework matches or outperforms several cutting-edge methods with more reliable training conditions in terms of important diagnostic criteria, such as accuracy 94 % and specificity 92 %.

Pavithra et al. [15] investigated the detection of skin cancer using SVM and CNN. Texture, color, and other features are extracted and then classified using the SVM approach. CNNs, on the other hand, can recognize intricate patterns because they automatically obtain spatial and hierarchical features from unprocessed images. In their investigation, the CNN classifier outperformed the SVM classifier with an accuracy of 95 91 %, while the SVM classifier only managed 94–30 %. The two-tailed significance value for the results was 0.000 ($p < 0.05$), indicating statistical significance.

Sachin Gupta et al. [16] utilized a dataset comprising 25,331 dermoscopic images with ground truth labels provided by the International Skin Image Collaboration (ISIC). They applied the Adaboost algorithm, this decreases the influence of misclassification loss on the convex upper bound of the replacement purpose. This approach incorporates dynamic training and testing enhancements, significantly improving the model's performance by iteratively adding appropriately weighted predictors. Their method segments the continuous amplitude of augmentations into equal-sized pieces to improve classification. Key metrics achieved include an F1 score of 0.62, a Positive Predictive Value (PPV) of 0.88, accuracy of 0.87, and sensitivity of 0.67. Traditional search methods for augmentation require training new models, which increases computational costs.

Wei et al. [17] proposed the Modified Thermal Exchange Optimization Algorithm, a metaheuristic method inspired by the temperature behavior of objects. This technique simulates temperature variations between warm and cold regions to update the locations. The region of interest was divided using the Otsu method, a popular thresholding technique. According to Newton's rule of cooling, an object's temperature updates are influenced by the pace at which its surroundings and body temperature change. Using this method, 20 distinct features were extracted for skin cancer diagnosis. The results achieved include an accuracy of 92.79%, sensitivity of 90.99%, PPV of 85.58%, and Negative Predictive Value (NPV) of 93.69%.

Navid et al. [18] introduced the Multi-agent Fuzzy Buzzard Algorithm (MAFBUZO) algorithm, which demonstrated effectiveness through minimal error values during minimization, ranging from 16.3459 to as low as 7.3258e-5. The study highlighted the challenges in accurately diagnosing skin conditions due to similarities in indicators, such as benign Clark lesions and malignant melanoma. The proposed method employed a sliding window approach to minimize system errors, achieving an accuracy of 0.94, sensitivity of 0.93, PPV of 0.88, and NPV of 0.95.

Gautam et al. [19] focused on Regional Information Patterns (ReIPs); a feature extraction technique designed to capture valuable regional information from the local neighborhood of image pixels. The Local Binary Pattern (LBP) technique demonstrated superior performance in various applications, particularly in computational efficiency and discriminative ability. Their study classified skin cancer using a linear SVM applied to dermoscopic images. Performance metrics on the ISBI2016_ISIC_Part3_Test_Data dataset include a precision of 93.51%, recall of 84.48%, and accuracy of 83.64%.

Lan et al. [20] introduced FixCaps-DS, a method that leverages residual learning to facilitate gradient flow through skip connections and shallow networks. The capsule layer in this architecture consists of two components: the primary capsule and the digit capsule. FixCaps, consistent with Capsule Networks (CapsNets), employs convolution in the primary capsule with an inner size of 9 and a stride size of 2. Experiments conducted on the HAM10000 dataset demonstrated that FixCaps achieved higher act compared to IRv2-SA, with an accuracy of 96.49%.

Lyakhov et al. [21] explored the combination of diverse data, integrating dermatological images with patient information like gender, age, and the location of a lesion on the body. This multimodal information underwent pre-processing to enhance Determine significant structures and adapt the data for neural network input. Their proposed system, utilizing the DenseNet_161 convolutional architecture, significantly reduced false negative predictions, a critical factor in identifying malignant skin lesions. The neural network system achieved an accuracy of 85–20%, highlighting the potential of combining image data with patient metadata for improved diagnostic outcomes.

Table 1. Analysis review of multiple classification techniques used in Skin Cancer

References	Name of Diseases Detection	Algorithm Applied	Output	Limitation
[22]	skin cancer detection	Deep Convolutional Neural Network (DCNN)	93.16% accuracy	Limited scalability for various types of skin and minority information.
[23]	Melanoma	Hybrid CNN and SVM	88.02% accuracy	less accuracy over state-of-the-art approaches.
[24]	Skin tumor classification	VGG16	0.88 F-score	Depending on a huge quantity of data labelled.
[25]	skin lesion localization	Feed-Forward Neural Network (HFaFFNN)	95.8% accuracy	Skin Lesion borders in complicated images

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2.1 PROBLEM STATEMENT

In the related work, various classification techniques have been employed, such as the SVM classifier, MAFBUZO algorithm, and CapsNet classification, for detecting skin diseases. Each technique has been estimated using performance metrics, but some problem remains. For example, accurately defining the detection rate and improving the classification of skin cancer stages whether normal or melanoma are still areas requiring attention. Detecting skin diseases based on appearance is particularly challenging, as skin lesions often show similar visual characteristics in some data set.

3. METHODS

The proposed method for detecting skin cancer is divided into three stages: segmentation, feature selection, and classification. This will involve using dermoscopy images from the MNIST HAM-10000 dataset to diagnose and categorize skin cancer into different groups using a CNN. The diagnostic process will utilize image classification and a deep learning approach. To improve the selective analysis of the training data, data scaling, balanced selection, and enhancement techniques will be utilized.

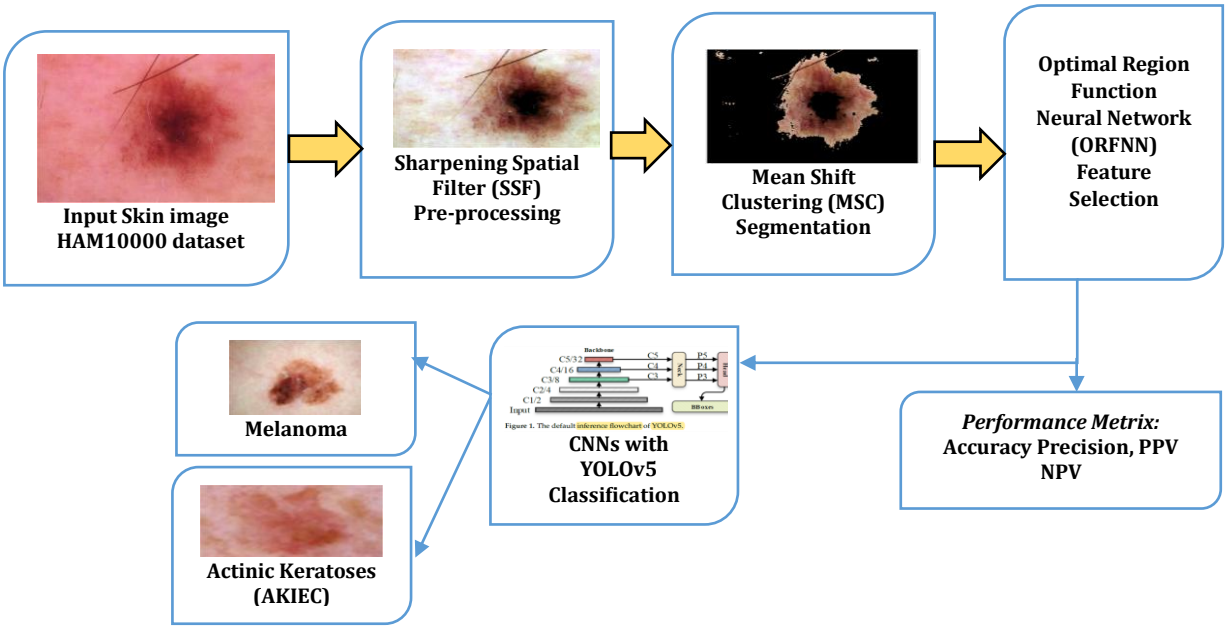

Figure 1. Methodology working Flow.

Figure 1 shows the novel proposed procedure for detecting skin cancer which involves image classification and segmentation. A Sharpening Spatial Filter (SSF) is used as a preprocessing method to reduce noise in the input image data set, this involves identifying and eliminating unsuitable noise. The lesion is then identified from both the outer and inner layers of skin and divided into clusters using Mean Shift clustering (MSC). From the segmentation, regions with similar characteristics are identified for feature selection using the Optimal Region Function Neural Network (ORFNN). CNN are used in deep learning for analyzing skin images and visual information and finding severity level and type of skin disease with the YOLOv5 classification technique.

3.1 Sharpening Spatial Filter (SSF) Preprocessing

A weighted average of each pixel's neighboring pixels is used to replace it. This approach is valuable because it simplifies the process of understanding its behavior, allows for easy customization to suit specific applications, and is straightforward to implement. In figure 2 shows the input image and filtered output image, which control the size and contrast of the structures to be preserved. Its non-iterative nature ensures that the constraints effects are applied directly, without compounding over multiple iterations, making the parameter-setting procedure more intuitive and efficient.

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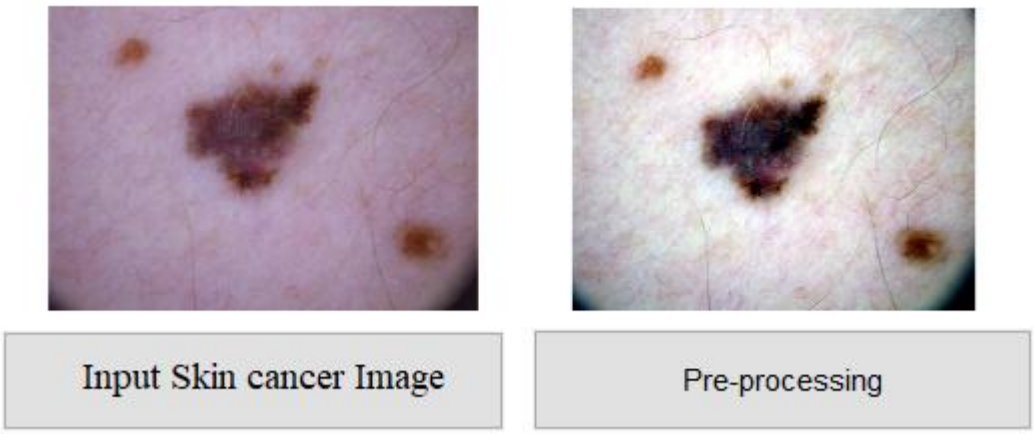

Figure 2. Skin cancer SSF Preprocessing output

$SF\,[I]_P = \frac{1}{w_P} \sum_{q \in s} G_{\sigma_S}(|P-Q|) - G_{\sigma r}(I_p - I_q) - I_q$ … (1)

In equation (1) A weighted average, the spatial $G_{\sigma s}$ reduces the impact of multi-layer of pixels, while the range Gaussian $G_{\sigma r}$ reduces the effect of pixels q whose intensity value differs from I_p.

$Z_{k+1} = Z_k\, \alpha e^i + D_{k+1}\, e^{i\emptyset}$ … (2)

In equation (2) where Z_k is identify the irregular pixel of the kth iteration, a is the color constant form different skin layer.

$\Delta_S f = \sum_{Q \in Q_s} W_Q \,.\, h_Q$ … (3)

For the smoothing the image equation (3) is calculated W_Q reconstructed windows obtained from the h_Q is pixel color variation.

3.2 Mean Shift Clustering (MSC) Segmentation

A clustering technique processes the preprocessed output of skin cancer images and divides it into several clusters representing the inner and outer layers, as illustrated in Figure 3. The pixel channels within each cluster are concatenated into a single vector. The region layer is then computed between the values within the filter's view, producing a single value for the corresponding output position. Conversely, a transpose convolution performs the reverse operation

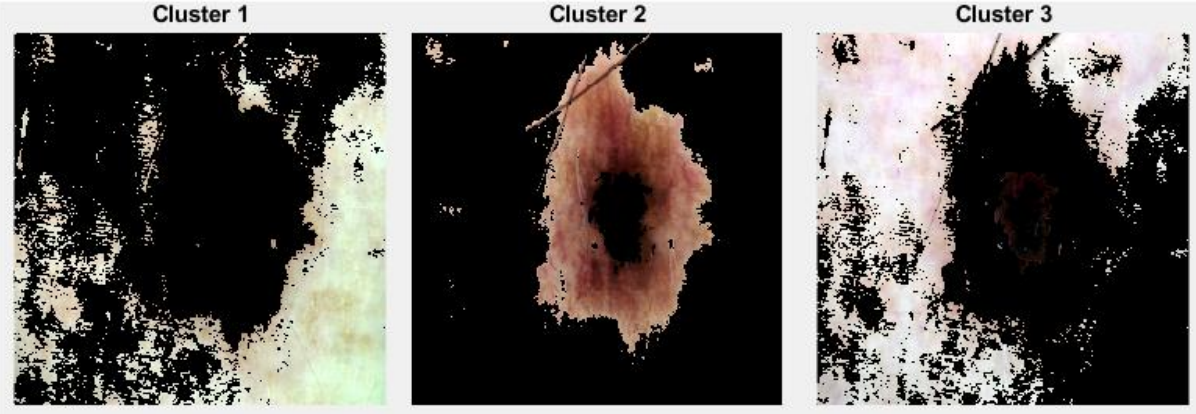

Figure 3. Three different clustered segmented outputs

The clustering approach, the image is divided into both front and back pixels are calculated based in equation (4).

$S_D = \{S_1, S_2 \ldots S_n\}$ … (4)

A skin region is calculated in equation (5) consists of a mean shift to convert the outcome to pixel wise dividing the estimations and receives the transformer's outputs.

$S = \text{skin region}(y_i^1)$ … (5)

In equation (6) calculates the pixel variation of dark and white layer of skin cancer affected are where q[x] is valuated the smaller are and x number of pixel taken.

$q[x] = \{ \frac{1\,(x=q)}{0\,(x \approx q)}$ … (6)

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Vol 25, No. 2 (2024)
http://www.veterinaria.org
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3.3 CNNs with YOLOv5 Classification

YOLO is a one-stage network that eliminates the need for a region proposal creation phase. It splits the input image into cells and generates bounding boxes and probabilities for each class. Each cell contains the X-coordinate and class information. To ensure accurate detection for various target sizes, the CNN uses multiple head scales to focus on small, medium, and large targets separately.

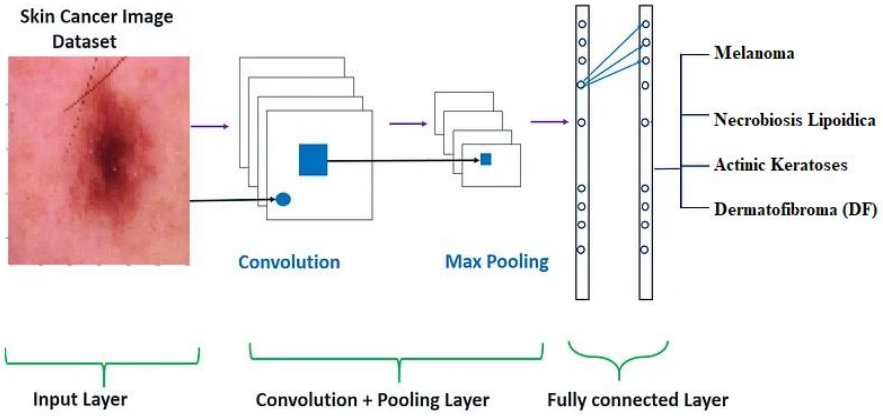

Figure 4. CNNs with YOLOv5 Classification architecture

In figure 4 the working of YOLOv5 approach, Input layer function reduces the image's dimensions by dividing the input image (which is preset at 640 × 640 × 3) into four 320 × 320 × 3 images. These images are then passed through convolutional + max pooling, along with slices and layers of convolution kernels, to produce a 320 × 320 × 32 image. The Fully connected layer maintains the integrity of the image while preventing it from being limited by the input size.

$$C_o = p\,(o)\,.\,IoU\,(b, o) \quad \ldots \quad (7)$$

In equation (7) C_o is probable that a thing is within the box is the IoU between the surface of skin and the predicted boundary.

$$L_{GIOU} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} I_{ij}^{obj} \left[1 - IoU + \frac{A^c - U}{A^c} \right] \quad \ldots \quad (8)$$

In equation (8) Where B is the amount of box limits in each pixel and *S*2 is the number of grids, where a region is inside the bounding box, the value of L_{GIOU} is equal to 1; otherwise, it will be 0.

$$L_{class} = -\sum_{i=o}^{S^2} I_{i,j}^{obiect} \quad \ldots \quad (9)$$

The confidence weight is I_{object} and the real confidence of the bounding box of j in the pixel size in skin cancer affected area calculated in equation (9).

$$IoU = \frac{B \cap B^{gt}}{B \cup B^{gt}} \quad \ldots \quad (10)$$

In equation (10) IoU is calculated the total area between bounding boxes is determined by a crossover over union characteristic. where B is the ratio of the detection box result's size to the region where the corresponding coordinates overlap.

4. RESULT AND DISCUSSION

This chapter explores the effectiveness of the CNN with YOLOv5 classification for identifying skin cancer images across various categories. The training accuracy of the model improves significantly towards the training and testing data matching. During the skin cancer image testing stage, a random skin lesion is selected and evaluated for accuracy and error rate. Table 2 displays the number of images used for testing and the software Python is utilized for skin cancer diagnosis through transfer learning.

Table 2. Simulation Parameter

Parameter	Value
Software	Python
HAM10000 dataset	600
Malignant	400
Testing image	200

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4.1 DATA SET

HAM10000 contains an extensive list of all the essential diagnostic standards for pigmented lesions. According to Tab, skin lesions come in seven different varieties. Figure 5 gives an example of labeled skin name appears that the labels are not dispersed equally because 5 (nv) is the most frequently used label. The other dataset was HAM10000, which is part of ISIC 2019. Using a multiple of preprocessing methods, it contains 1000 dermatoscopic images captured at different locations.

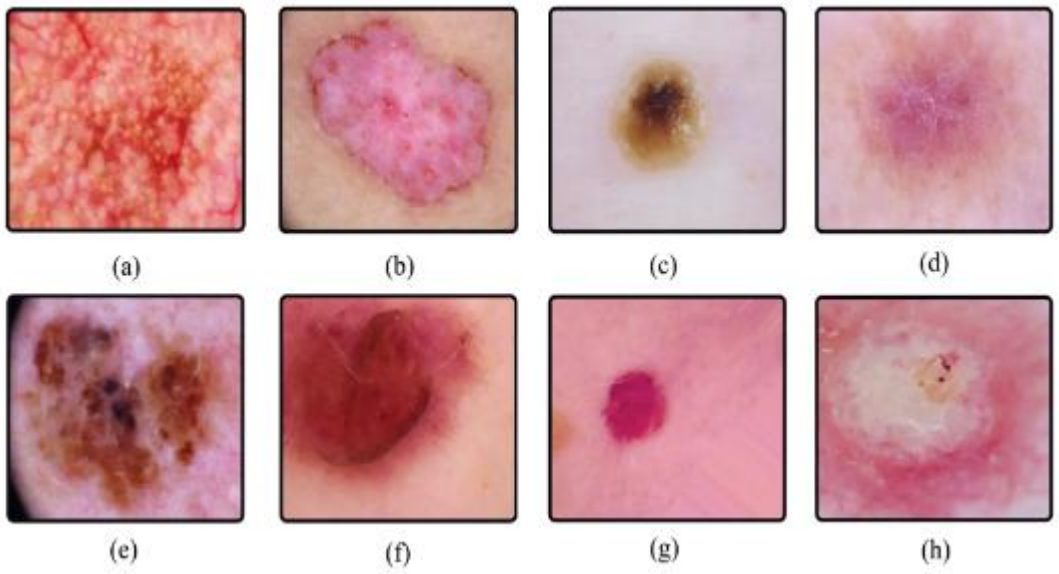

Figure 5. Illustrations of each class in ISIC 2019 (a–h) and HAM10000 (a–g). AKIEC, BCC, DF, MEL, NV, VASC, and sec are the first five

4.2 COMPRASION ANALYSIS

Three distinct performance metrics are compared in the analysis below: error rate, accuracy, PPV, and NPV. The CNN with YOLOv5 classifications is better based on these output values than on earlier research from the literature, as shown below

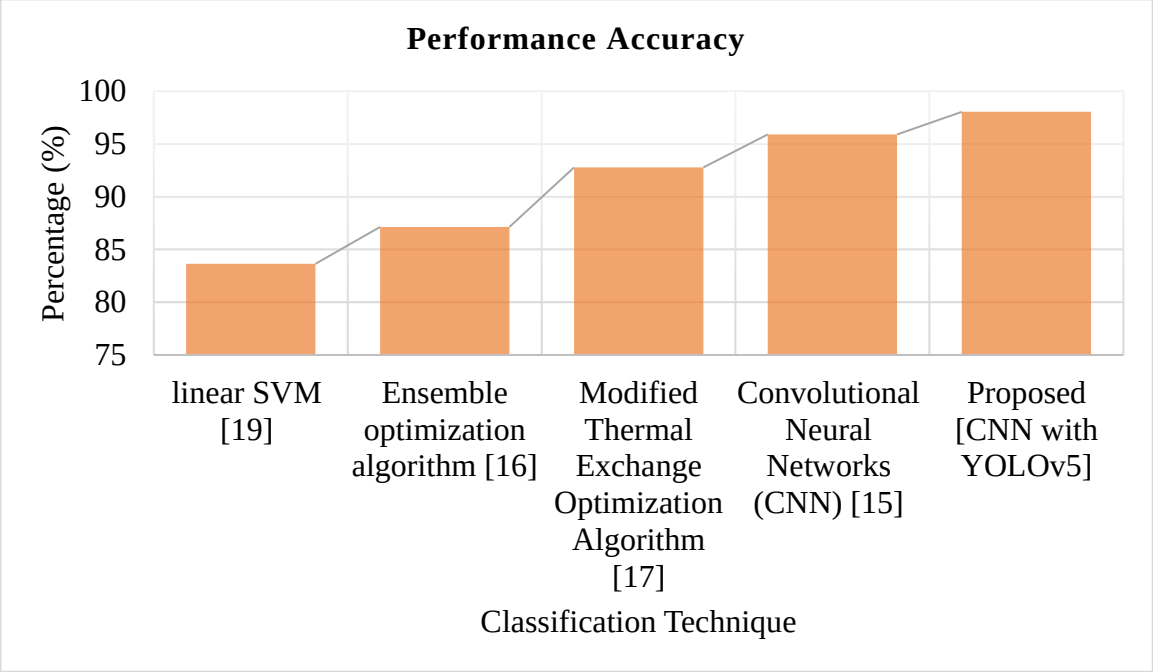

Figure 6. performance of Accuracy

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Vol 25, No. 2 (2024)
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Figure 6 shows the different classification techniques and their corresponding accuracy percentages. The Linear Support Vector Machine (SVM) achieved an accuracy of 83.64%, followed by the Ensemble Optimization Algorithm with an accuracy of 87.15%. The Modified Thermal Exchange Optimization Algorithm showed a significant improvement with a higher accuracy of 92.79%. CNN performed even better, reaching an accuracy of 95.91%. Finally, the proposed model, which combines CNN with YOLOv5, achieved the highest accuracy at 98.05%. This progression indicates the increasing effectiveness of more advanced algorithms in classification processes.

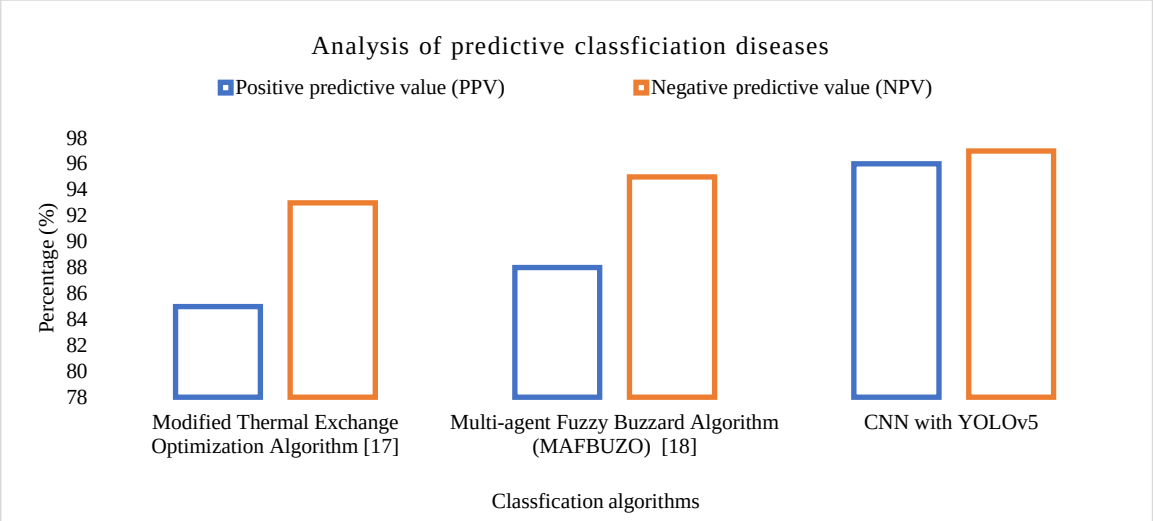

Figure 7. Evaluation of NPV and PPV

Figure 7 shows the NPV and PPV comparison with proposed and previous methods, The Modified Thermal Exchange Optimization Algorithm achieved a PPV of 85, indicating a relatively strong ability to correctly identify positive instances. The MAFBUZO showed an improvement, with a PPV of 88, reflecting its higher precision in identifying positive cases. The improved PPV of 96 was achieved by the combination of CNN with YOLOv5, demonstrating its superior capability in accurately predicting positive outcomes.

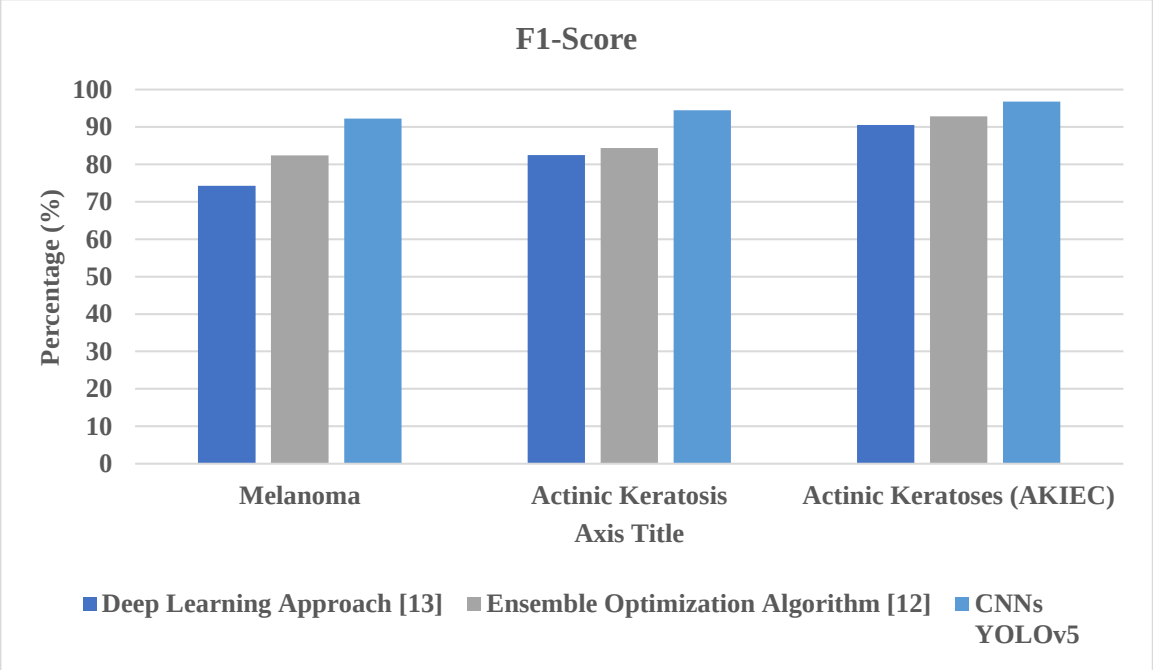

Figure 8. F1 Score analysis

Figure 8 shows the dataset in which Melanoma, Actinic Keratosis, and Actinic Keratoses (AKIEC) were evaluated with classification algorithms, and proposed CNN and yolov5 improved performance metrics.

5. Conclusion

The present work summarizes a skin cancer classification method that utilizes CNN and yolov5 on various skin cancer diseases images, and compares with previous classification approach. The study categorizes skin cancer into four types, which is a commonly used classification system. Our training and testing strategy have been improved through meticulous preparation processes, Effective data augmentation approaches, and the use of a Yolov5 neural network design. The results, with an accuracy of 98.05 %, precision of 96%, specificity of 96%, PPV of 96.55%, and NPV of 96.45%, demonstrate the effectiveness of our technique in detecting skin cancer. The proposed Yolov5 classification is improved and enhanced by neural network-based approaches and skin cancer severity level identification is improved.

5.1 Future scope

In the future, it is important to focus more on the advancements in artificial intelligence for the detection of various skin cancer diseases. Integrating AI into skin cancer classification presents a significant opportunity to improve diagnostic precision and effectiveness. Early detection and accurate diagnosis are crucial for skin cancer treatment. Traditional methods have been shown to be effective in detecting and identifying skin cancer. Furthermore, advanced machine learning techniques can identify the severity and types of skin cancer, with a focus on recognition, classification, and localization.

REFERENCES

[1] S. Ozturk and T. Çukur, “Deep clustering via center-oriented margin free-triplet loss for skin lesion detection in highly imbalanced datasets”, IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 9, pp. 4679-4690, 2022.
[2] K. M. Hosny, D. Elshoura, E. R. Mohamed, E. Vrochidou and G. A. Papakostas, “Deep Learning and Optimization-Based Methods for Skin Cancer Segmentation: A Review”, in IEEE Access, vol. 11, pp. 85467-85488, 2023.
[3] N. Nigar, M. Umar, M. K. Shahzad, S. Islam and D. Abalo, "A deep learning approach based on explainable artificial intelligence for skin lesion classification”, in IEEE Access, vol. 10, pp. 113715-113725, 2022.
[4] H. L. Gururaj, N. Manju, A. Nagarjun, V. N. M. Aradhya and F. Flammini, "Deep Skin: A deep learning approach for skin cancer classification", in IEEE Access, vol. 11, pp. 50205-50214, 2023.
[5] Rajeshwari, J., and M. Sughasiny, “Modified filter-based feature selection technique for dermatology dataset using beetle swarm optimization”, EAI Endorsed Transactions on Scalable Information Systems 10, no. 2, 2023.
[6] Islam, Md Sirajul, and Sanjeev Panta. "Skin cancer images classification using transfer learning techniques”, arXiv preprint arXiv, 2024.
[7] Aldi, Febri. "Extraction of shape and texture features of dermoscopy image for skin cancer identification”, Sinkron: Jurnal dan Penelitian Teknik Informatika, no. 2, pp. 650-660, 2024.
[8] Wu, Y., Chen, B., Zeng, A., Pan, D., Wang, R., and Zhao, S, “Skin cancer classification with deep learning: a systematic review”, Frontiers in Oncology, 2022
[9] R. Karthik, R. Menaka, S. Atre, J. Cho and S. Veerappampalayam Easwaramoorthy, “A hybrid deep learning approach for skin cancer classification using swin transformer and dense group shuffle non-local attention network”, IEEE Access, vol. 12, pp. 158040-158051, 2024.
[10] M. A. Khan, K. Muhammad, M. Sharif, T. Akram and V. H. C. d. Albuquerque, “Multi-Class skin lesion detection and classification via tele dermatology”, IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 12, pp. 4267-4275, 2021.
[11] M. Gallazzi, S. Biavaschi, A. Bulgheroni, T. M. Gatti, S. Corchs and I. Gallo, “A large dataset to enhance skin cancer classification with transformer-based deep neural networks”, IEEE Access, vol. 12, pp. 109544-109559, 2024.
[12] Y. Nie, P. Sommella, M. Carratù, M. Ferro, M. O’Nils and J. Lundgren, “Recent advances in diagnosis of skin cancer using dermoscopic images based on deep learning”, IEEE Access, vol. 10, pp. 95716-95747, 2022.
[13] S. Vachmanus, T. Noraset, W. Piyanonpong, T. Rattananukrom and S. Tuarob, “DeepMetaForge: A Deep Vision-Transformer Metadata-Fusion Network for Automatic Skin Lesion Classification”, IEEE Access, vol. 11, pp. 145467-145484, 2023.
[14] Bakheet, S.; Alsubai, S.; El-Nagar, A.; Alqahtani, A, “A multifeatured fusion framework for automatic skin cancer diagnostics”, Diagnostics, 2023.
[15] Pavithra, A., and B. T. Geetha. “Detection of skin cancer using support vector machine classifier compare with convolutional neural network classifier based on accuracy”, AIP Conference Proceedings, vol. 2821, no. 1, AIP Publishing, 2023.
[16] Sachin Gupta, Jayanthi R, Arvind Kumar Verma, Abhilash Kumar Saxena, Alok Kumar Moharana, Shubhashish Goswami, “Ensemble optimization algorithm for the prediction of melanoma skin cancer”, Measurement: Sensors, vol. 29, 2023.
[17] Wei, L., Pan, S. X., Nanehkaran, Y. A., and Rajinikanth, V, “An optimized method for skin cancer diagnosis using modified thermal exchange optimization algorithm”, Computational and Mathematical Methods in Medicine, 2021.

[18] Navid Razmjooy, Ali Arshaghi, “Application of multilevel thresholding and CNN for the diagnosis of skin cancer utilizing a multi-agent fuzzy buzzard algorithm, Biomedical Signal Processing and Control, Volume 84, 2023.
[19] Gautam, Anjali, and Balasubramanian Raman, “Towards accurate classification of skin cancer from dermatology images”, IET Image Processing, pp. 1971-1986, 2021.
[20] Z. Lan, S. Cai, X. He and X. Wen, "FixCaps: An Improved Capsules Network for Diagnosis of Skin Cancer," in IEEE Access, vol. 10, pp. 76261-76267, 2022.
[21] P. A. Lyakhov, U. A. Lyakhova and D. I. Kalita, “Multimodal analysis of unbalanced dermatological data for skin cancer recognition”, IEEE Access, vol. 11, pp. 131487-131507, 2023.
[22] Md Shahin Ali, Md Sipon Miah, Jahurul Haque, Md Mahbubur Rahman, Md Khairul Islam, “An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models”, Machine Learning with Applications, Volume 5, 2021,
[23] Duggani Keerthana, Vipin Venugopal, Malaya Kumar Nath, Madhusudhan Mishra, “Hybrid convolutional neural networks with SVM classifier for classification of skin cancer, Biomedical Engineering Advances, vol. 5, 2023.
[24] Bechelli, S.; Delhommelle, J, “Machine learning and deep learning algorithms for skin cancer classification from dermoscopic images”, Bioengineering 2022.
[25] Khan, Muhammad Attique, Tallha Akram, Muhammad Sharif, Seifedine Kadry, and Yunyoung Nam, “Computer Decision Support System for Skin Cancer Localization and Classification”, Computers, Materials and Continua 68, no. 1, 2021.