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Enhancing Skin Lesion Classification using Deep Learning Features and Genetic Algorithm-Optimized Cosine Weighted KNN

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Abstract: The effective care of skin cancer relies on the fine detection of skin lesions. Deep learning techniques are increasingly being used in medical diagnosis, ranging from the classification of skin lesions. Their ability to learn deep discriminative features from dermoscopic images is what makes them popular. In spite of the fact that deep learning approaches learn rich semantically rich information, the approaches currently being taken tend to suffer from poor generalization, high levels of redundancy, and KNN classifiers that assign identical weights to all neighbors. The paper proposes a new approach using machine learning for the classification of skin lesions, entailing deep feature extraction, techniques for dimensionality reduction, and approaches for optimization. Specifically, the ResNet50 architecture using Global Average Pooling for deep feature extraction from dermoscopic images will be employed. The most relevant and non-redundant features are identified through the Minimum Redundancy Maximum Relevance (mRMR) method. mRMR removes irrelevant class information and reduces the feature size considerably. A new approach for the KNN classifier substitutes the fully connected layer of ResNet50. The weights for instance and feature levels are computed with the Genetic Algorithm (GA) and the use of cosine similarity. The proposed approach attains a high accuracy of 90.61% on the classification task for the binary images of skin lesions. The experimental results show that the proposed optimized cosine weighted KNN approach is effective for the diagnosis of skin cancer.

Keywords: Skin Lesion Classification, ResNet50, mRMR, Cosine Similarity, Genetic Algorithm, Weighted K-Nearest Neighbors.

1. Introduction

Skin cancer is considered to be one of the serious health issues worldwide resulting in a large mortality rate. World Health Organization (WHO) stated that up to 10 million people are affected due to skin cancer per year. Prompt and proper diagnostic approach would help; otherwise, the rate of skin cancer will dramatically increase over the next two decades [1]. In the world-wide skin cancer was found as the fifth most commonly diagnosed form of cancer. Increase in the skin cell resulting in the development of tumors. The tumor can be distinguished in two forms: firstly, known as benign which causes proper cell divisions without affecting the neighboring tissues; another form known as malignant which causes rapid cell divisions resulting in attacking neighboring tissues as well as invading other parts of the body [2].

The melanoma is taken into consideration to be the most dangerous disease among all the others type of skin cancer. It comprises approximately 5% of all the types of skin cancer but causes 80% of all deaths. There are 55,500 annual deaths reported worldwide due to skin

cancer [3, 4]. The prognosis of the case of advanced melanoma is not very bright. In most of the untreatable situations, fewer than 20% of the patients were able to live for a span of five years [5]. However, if the condition of the melanoma is detected early, then the survival percentage goes up to 95% [6].

Traditionally, the diagnosis of skin cancer is highly reliant on the examination of lesions by trained dermatologists achieved through histopathological analysis. Although it is efficient, there are some challenges such as subjectivity, potential for discrepancies, as well as the manual intensity of the process, in addition to the potential for the diagnosis to result in a delay in treatment. Moreover, manual diagnosis of skin cancer is challenging in view of the complex morphological patterns derived from the thermoscopic images. This results in reliance on computer aids for analysis of the skin [7].

Over the last years, deep learning-based computer-aided diagnostic systems have emerged as powerful tools that can perform skin lesion classification tasks with high accuracy and consistency [8]. Among

deep convolutional neural networks, the architecture of ResNet50 has proved its exceptional performance in feature extraction due to their deep hierarchical representations combined with residual learning mechanisms [9]. However, high-dimensionality features extracted from deep networks can introduce redundancy and noise, which in turn negatively impact model generalization. This can be addressed through the feature selection techniques like Mutual Information, which retains the most informative features and also reduces dimensionality and computational cost [10].

In particular, the final classification stage of CAD systems is important. The traditional KNN algorithm, though simple and intuitive, does not utilize the full potential of the high-dimensional and imbalanced data contexts in learned features [11]. Cosine similarity as a distance metric can capture the angular relations in high-dimensional feature space quite well, and hence it is especially apt for the CNN-derived embeddings [12].

The deep learning-based systems rely purely on the CNN softmax classifier or adopt unweighted KNN approaches that do not take into account feature redundancy or sample level variability. Previous hybrid approaches of CNN and KNN do not consider optimized weighting while most ignore the feature relevance role in high dimensional spaces. More deep feature extractions normally introduce feature correlation that reduces discriminative power.

This paper proposes a new hybrid diagnostic model, which integrates ResNet50-based feature extraction with Minimum Redundancy Maximum Relevance-based feature selection. Moreover, it introduces a new classifier, Cosine Weighted KNN, replacing the fully connected layer in ResNet50. It will embed feature-level importance based on mutual information and instance-level weighting with cosine distance while performing weights optimization using the Genetic Algorithm. In this way, this new approach is evaluated on the dermoscopic image dataset for promising results in terms of accuracy, precision, recall, and F1-score. Thus, this proves that the proposed approach has the potential for automated diagnostics in skin cancer.

2. Review of Literature

The combination of deep learning and optimization techniques results in significant advancement in skin lesion classification. The Convolutional Neural Networks (CNNs) are the cornerstone in skin cancer diagnosis. Several studies have been carried out on various architectures to improve classification accuracy particularly for melanoma and other critical skin lesion types.

Results by Rasel *et al.* [13] mention the crucial role of nonlinear activation functions in CNNs and proves that the parameterized Leaky ReLU function could

enhance melanoma recognition under limited data conditions by achieving 97.50% accuracy. In the same way, Albahar [14] proposed a CNN model including a novel regularizer which yields high diagnostic accuracy showing better performance in binary lesion classification tasks. Transfer learning also plays an important part in skin lesion classification. Dimililer and Sekeroglu [15] showed that without augmentation, too, the models trained on smartphone images could still achieve significant improvement in classification accuracy and attain an accuracy of 86%. Similarly, issues like data imbalance and noise have been tackled through ensemble methods and preprocessing strategies by Selvaraj *et al.* [16], achieving a macro-average ROC-AUC of 97%. It highlights the significant role of the ensemble deep learning models towards skin lesion classification.

A new Fused KNN classifier named Fused KNN has been developed for the detection of melanoma, which is a combination of NN, and 7-NN predictions. The diagnostic accuracy of the model has been improved by methods such as similarity indexing and overlapping. It was tested on 12 cancer datasets and outperforms the conventional classifiers by obtaining a classification accuracy of 97.8% [17]. An image-based approach for the detection of the skin cancer was proposed that utilize the HAM10000 dataset with a total of 10,015 images. The features extracted from these dermoscopic images were classified based on the KNN and XGBoost algorithms. kNN performed better with 73% accuracy as compared to the XGBoost method for the classification of the above-stated features. We believe this adds to its value that it suggests the early detection of skin lesions, thereby providing adequate medical attention to them [18].

The Genetic Optimization based Supervised K-Nearest Neighbor algorithm named MGO-SKNN was introduced to diagnose skin diseases accurately from clinical images. The image preprocessing techniques were applied and the features were extracted using the GLCM method. This proposed approach outperformed the traditional methods with the 97.53% classification accuracy. It enhances the diagnostic efficiency and supports for better treatment planning [19].

A research paper proposes a deep learning hybrid model for effective skin cancer diagnosis by dermoscopic images. It employs DeepLabV3+ for precise lesion segmentation and used MobileNetV2, EfficientNetB0, and DenseNet201 for feature extraction. The ReliefF algorithm was utilized for feature selection and then the KNN algorithm was applied for classification. The proposed model obtains an accuracy of 94.42% on the ISIC 2019 dataset and 94.44% on the PH2 performs better than the individual models [20]. The system based on MATLAB was developed to categorize skin lesions using the K-nearest neighbor algorithm. The KNN algorithm achieved high classification accuracy of

98% which proved its potential for reliable and efficient skin cancer diagnosis [21].

In the above works, mainly the role of CNNs and transfer learning for the classification of skin lesions is addressed. Nevertheless, in the proposed work, a novel technique using deep features of ResNet50, Maximum Relevance (mRMR) feature selection, and a Weighted KNN technique with cosine similarity using Genetic Algorithm for optimization is introduced. This work shows better results for the above-said skin lesion classification.

3. Methodology

In this work, the authors are proposing a skin lesion classification technique by combining deep feature extraction with ResNet50, feature selection using mRMR, and the Cosine Similarity-based Weighted K-Nearest Neighbor (KNN) classifier. The weights involved in classification are optimized using the Genetic Algorithm (GA).

3.1 Dataset

The proposed model performance in this study was evaluated on the skin cancer image dataset, which is publicly available on Kaggle [22]. There are two primary subsets in the dataset, namely training and testing, categorized into benign and malignant classes. Distribution of images across these subsets is as per Table 1 below [23].

Table 1. Details of the number of images used to develop the proposed model

Class	Train	Test	Total
Malignant	1197	300	1497
Benign	1440	360	1800
Total	2637	660	3297

There are 2637 images for training and 660 images for testing. It gives a fair view of both benign and malign examples that can be used for model development and testing. Some of the sample images selected from the dataset are shown below in Figure 1.

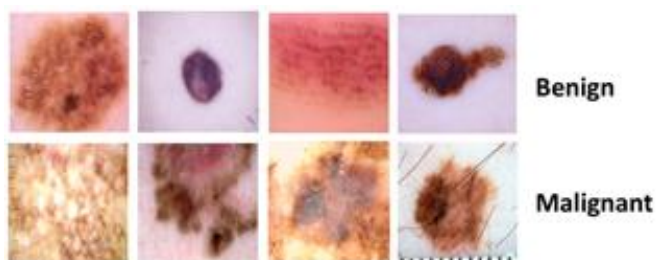


Figure 1. Selected sample from Dataset

3.2 Deep Feature Extraction using ResNet50

ResNet50 is the popular convolutional neural network (CNN) architecture which is used for feature extraction from the image dataset. It comprises of 50 layers and comprises identity shortcut connections. It allows gradients to propagate effectively across layers. This is well-suited for deep feature extraction tasks in medical imaging dataset.

In the proposed work, the use of the ResNet50 model, which was pre-trained on the ImageNet dataset, is considered for fixed feature extraction. This technique utilizes the concept of transfer learning, in which the insights acquired from the massive amount of natural image datasets are implemented for the dermoscopic image dataset. The original classification part of the ResNet50 model is discarded, replacing it with the use of the Global Average Pooling (GAP) layer, which compresses the spatial representation of the feature maps to a scalar value by finding the average of each feature map. The structure of the ResNet50 model is depicted in Figure 2.

Let $F \in R^{7 \times 7 \times 2048}$ denote the final convolutional output of ResNet50 for an input image I . The GAP process converts F into a 2048-dimensional vector $f_i \in R^{2048}$ as follows:

$$f_i[j] = \frac{1}{49} \sum_{x=1}^7 \sum_{y=1}^7 F_{x,y,j}, \text{ For } j = 1, 2, \dots, 2048 \quad (1)$$

This collective feature vector captures high level abstract semantic features of the input image and discarding spatial information. The reduction in the number of trainable parameters, minimization of overfitting risk and preservation of robust global features are the benefits of using GAP.

The GAP layers are fundamentally invariant to minor translations in the input image. This is an advantage in dermoscopic image analysis where lesion localization may vary slightly. These 2048-dimensional feature vectors extracted from each image will be the inputs for the subsequent stages like feature selection and classification.

This step converts the raw image data into rich, discriminative and compact representations of features. These are appropriate for feature selection and optimized classification techniques.

3.3 Feature Selection using mRMR

This study adopts the Minimum Redundancy Maximum Relevance (mRMR) technique for feature selection which is reduce the dimensionality and enhance generalization. The mRMR is used to select the highly informative features with minimum redundancy with each other.

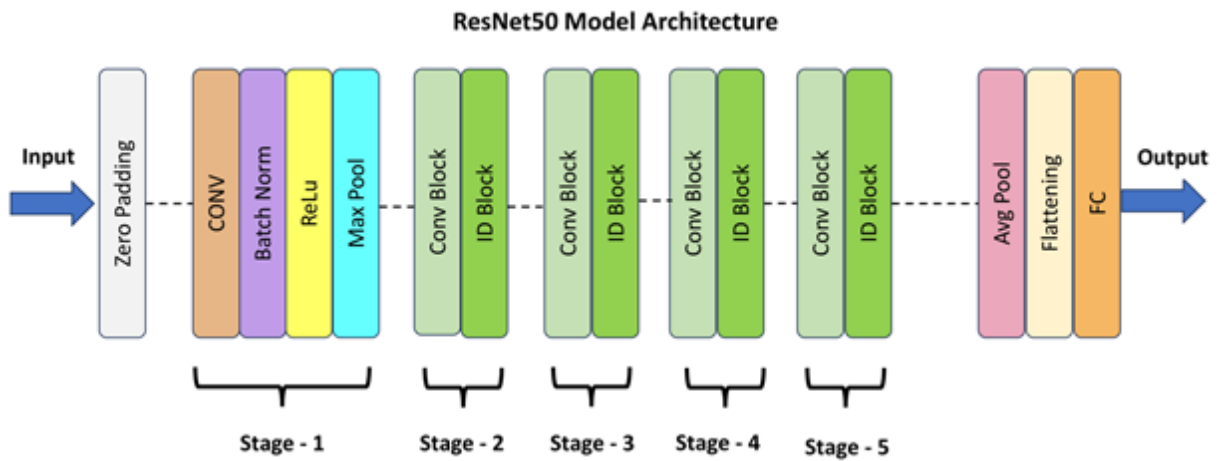


Figure 2. ResNet50 Architecture

In each iteration the subsequent feature f_j is selected by maximizing the following score:

$$mRMR(f_j) = I(f_j; Y) - \frac{1}{|S|} \sum_{f_s \in S} I(f_j; f_s) \quad (2)$$

Where:

- $I(f_j; Y)$ denotes the mutual information between feature f_j and the target class Y which represents the relevance between them.
- S is the set of features already selected.
- $I(f_j; f_s)$ represents the mutual information between feature f_j and each previously selected feature $f_s \in S$ which measures the redundancy among them.
- $|S|$ is the number of selected features.

This scoring function ensures that the selected features contribute unique and corresponding information. In addition, it improves the discriminative power of the subsequent classifier by avoiding overfitting. In this study, the top m features based on the mRMR scores are retained to construct a reduced feature matrix of size $n \times m$, where n is the number of image samples.

The term $\frac{1}{|S|} \sum_{f_s \in S} I(f_j; f_s)$ in the mRMR score penalizes redundancy by measuring the average mutual information between the candidate feature and the already selected features. A high value of this term indicates that the feature is highly correlated with existing ones. It will add only the very less new information. Thus, the selection of features is not only relevant to the target but also diverse from one another.

3.4 Cosine Similarity and Cosine Distance Estimation

In this study, cosine similarity is employed as the distance metric. It effectively measures the angular closeness between feature vectors obtained from the

mRMR selected subset of deep features. Before similarity computation all feature vectors are L2-normalized to ensure that the comparison is scale-invariant.

Let x be the normalized feature vector of a test sample and x_i be the normalized feature vector of a training sample. The cosine similarity between them is computed as follows:

$$\cos_sim(x, x_i) = \frac{x \cdot x_i}{\|x\| \cdot \|x_i\|} \quad (3)$$

The corresponding cosine distance is:

$$\cos_dist(x, x_i) = 1 - \cos_sim(x, x_i) \quad (4)$$

The cosine distances are calculated between each test sample and all training samples and stored in a distance matrix. This precomputed matrix is used during the entire classification process to find the k -nearest neighbors for each test instance. The use of cosine distance effectively captures angular relations in the high-dimensional feature space and making it well-suited for deep feature obtained from convolutional neural networks.

3.5 Genetic Algorithm for Weight Optimization

A Genetic Algorithm (GA) is employed to optimize both instance and feature weights to enhance the performance of the Cosine Similarity based Weighted KNN classifier. Each individual in the GA population is encoded as a real valued vector which contains n instance weights and m feature weights:

$$\text{Individual} = [w_1, w_2, \dots, w_n, f_1, f_2, \dots, f_m]$$

The classification accuracy is used in the fitness function to evaluate an individual I on the validation set.

$$\text{Fitness}(I) = \text{Accuracy}(y, \hat{y}) = \frac{1}{n} \sum_{i=1}^n 1(\hat{y}_i = y_i) \quad (5)$$

Where \hat{y}_i the predicted class are labels, y are the actual class labels, n is the number of validation samples, and $1(\cdot)$ is the indicator function. The standard

GA operators such as two-point crossover, Gaussian mutation and tournament selection are applied to iteratively evolve the population. This approach enables to find the optimal weights for improving model generalization and classification accuracy.

3.6 Weighted Likelihood Estimation and Classification

In the proposed GA-Optimized Cosine Weighted K-Nearest Neighbor (OCWKNN) model, the final classification decision is made using a weighted likelihood estimation scheme which combines both instance-level and feature-level weights contributions. The cosine similarity is computed between the normalized feature vectors of the test sample and all training samples. It has been used as the instance-level weight which reflects the angular similarity between samples. Feature-level weights are obtained from the Minimum Redundancy Maximum Relevance (mRMR) method which selects the top m most informative and least redundant features. These weights are optimized using the Genetic Algorithm (GA) for improving the classification performance.

Let x be a test data and N_k represent its k nearest neighbors obtained by cosine similarity. The weighted likelihood for assigning x to class C_i is calculated as follows:

$$P(C_i | x) \approx \left(\sum_{j \in N_k} \delta(y_j = C_i) \cdot \frac{w_j}{d_j} \right) \cdot \left(\sum_{d=1}^m f_d \cdot MI_d \right) \quad (6)$$

Where:

- $\delta(y_j = C_i)$ is an indicator function that equals 1 if the label of neighbor j is C_i and 0 otherwise.
- d_j is the cosine distance between test sample x and neighbor x_j .
- w_j is the GA-optimized instance weight corresponding to neighbor j .
- f_d is the GA-optimized feature weight for feature d .
- MI_d is the mutual information score for feature d , obtained via mRMR.
- $\sum_{d=1}^m f_d \cdot MI_d$ acts as a global relevance score representing the weighted contribution of selected features.

This likelihood function guarantees that the neighbors with higher angular similarity (i.e., lower cosine distance d_j) and greater reliability (i.e., larger instance weight w_j) contribute more meaningfully to the classification. In addition, the global feature relevance is estimated through a weighted combination of mRMR scores and Genetic Algorithm-optimized feature weights. The OCWKNN model enhances its capability for the accurate diagnostics by combining local instance influence with global feature importance.

3.7 Model Evaluation

The best weights obtained from GA are used for testing the final model on standard metrics like accuracy, precision, recall, and F1-score. A performance accuracy is calculated, which is stated to be the ratio of correct predictions to the total number of predictions.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP} \quad (7)$$

Precision measures the proportion of the true positives among all positive predictions.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (8)$$

Recall measures the amount of the true positives predicted among all actual positives.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (9)$$

F1-score is the harmonic mean of precision and recall. It provides the balanced measure when there is an uneven class distribution.

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (10)$$

These metrics provide the comprehensive assessment of the classification performance of the algorithms.

4. Proposed Algorithm

The proposed algorithm combines deep learning and evolutionary optimization technique for enhancing the skin lesion classification performance. It includes ResNet50-based deep feature extraction, Mutual Information-based feature selection and the Genetic Algorithm optimized Cosine Weighted KNN classifier. The step-by-step procedure of the proposed OCWKNN method is outlined in Figure 3.

From Figure 3 the proposed GA-Optimized Cosine weighted K-Nearest Neighbor (OCWKNN) algorithm includes the following key steps.

Step 1: Extract the deep features from the dermoscopic images by using the pre-trained ResNet50 model with Global Average Pooling.

Step 2: Calculate the significance of each feature by using the Minimum Redundancy Maximum Relevance (mRMR) algorithm and select the top m informative and non-redundant features.

Step 3: Estimate the cosine similarity between the normalized feature vectors of each test sample and all training samples by using equation (3) and derive the cosine distance from it by using equation (4).

Step 4: Identify the k nearest neighbors that is based on the lowest cosine distance values.

Step 5: Estimate the class wise weighted likelihood by combining the instance and feature weights that are optimized by Genetic Algorithm (using equation (6)).

Step 6: Predict the class label by selecting the class with the highest aggregated weighted likelihood score from the k neighbors.

This proposed OCWKNN technique is effectively integrates deep feature extraction, mRMR-based feature selection and GA-optimized weighting to enhance classification performance.

5. Results and Discussion

The aim of this research was to improve the efficiency of classification algorithms with the help of the proposed Optimized Cosine Weighted K-Nearest Neighbor (OCWKNN) approach. This section will present the results of analysis on the efficiency of the proposed approach and its comparison with the current best models used in skin lesion dataset prediction.

Evaluation of the performance of the proposed Optimized Cosine Weighted K-Nearest Neighbor (OCWKNN) algorithm is carried out on the skin cancer dataset, which contains the binary class labels, for example, benign and malignant. Confusion Matrix is shown in Figure 4.

Out of 360 benign samples 326 were correctly classified and 34 were misclassified as malignant. For malignant cases, 272 were correctly identified out of 300 samples and 28 misclassified as benign.

Table 2 provides the performance of the classification concerning precision, recall, and F1-score of benign and malignant skin lesions.

The proposed OCWKNN model shows the consistent performance across both benign and malignant skin lesion classes. The benign class shows slightly higher precision which indicates better identification of true benign cases. At the same time, the malignant class achieves a higher recall value which suggesting the effective detection of true malignant cases with minimal false negatives which is very important for clinical applications. The close alignment of precision and recall across classes proves the model robustness and the high unweighted average F1-score confirms its overall reliability.

Table 3 depicts that the proposed OCWKNN outperformed other existing state-of-the-art methods reported in [23] conducted on the same dataset with accuracy of 90.61%. Since the dataset used in this research is well balanced, accuracy has been considered as a suitable evaluation metric.

Figure 5 graphically represents the performance improvement of the proposed OCWKNN algorithm compared to other state-of-the-art approaches.

The use of cosine similarity along with carefully weighted features and samples and also optimized using evolutionary algorithms is highly useful for the model to differentiate even small differences between skin lesion types in dermoscopic images. This indicates that fine-tune sample insights and also the meaningful feature contribution can significantly enhance classification performance in medical image analysis tasks.

Table 2. Summary of results (%) obtained for different classes

Class	Precision	Recall	F1-score
Benign	92.03	90.56	91.29
Malignant	88.89	90.67	89.77
Unweighted average	90.46	90.62	90.53

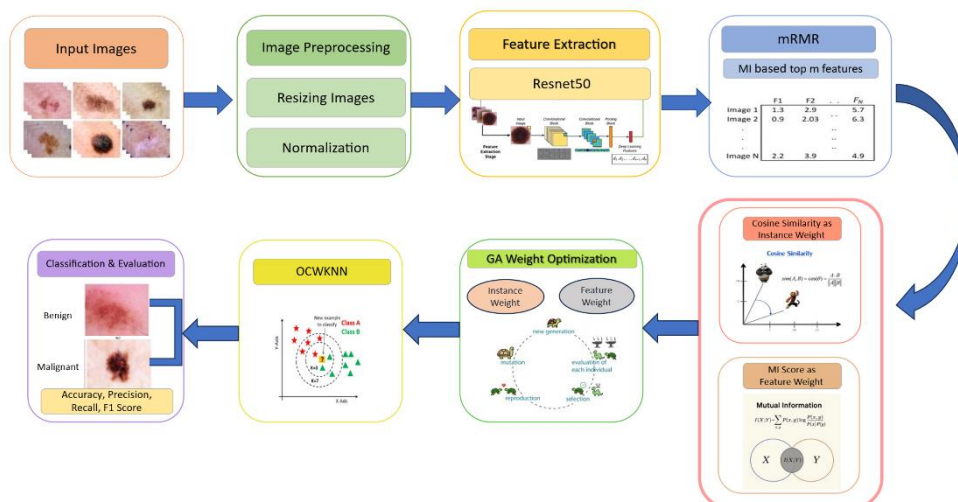


Figure 3. Proposed OCWKNN model

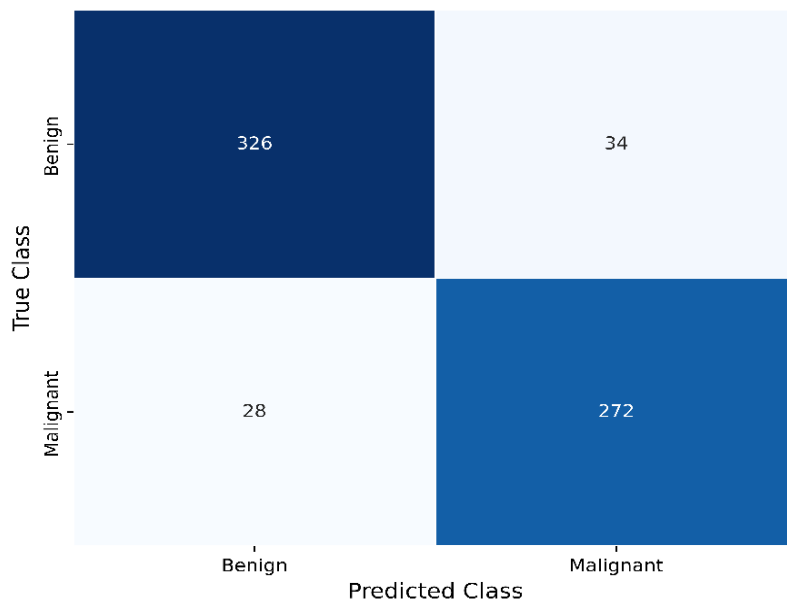


Figure 4. Confusion Matrix Obtained using the Test Data

Table 3. Comparison of Our Proposed Method with Other State-of-the-Art Methods using the Same Dataset.

Year	Study	Method(s)	Classifier / Activation function	Accuracy (%)
2021	Abdar <i>et al.</i> [24]	Binary residual feature fusion	Softmax	89.24
2021	Abdar <i>et al.</i> [25]	Three-way decision- based Bayesian deep learning	Softmax	88.95
2021	Gupta <i>et al.</i> [26]	Inceptionv3	Neural network	83.20
2022	Anand <i>et al.</i> [27]	VGG16	Softmax	89.09
2022	Salian and Sawarkar [28]	EfficientNetB3	Softmax	87.12
2023	Ramya and Sathiyabhama [29]	Enhanced genetic algorithm, extreme learning machine, ResNet50	SVM	89.19
2023	Hussein <i>et al.</i> [30]	ResNet-18	Softmax	89.39
2023	Shekar and Hailu [31]	DenseNet-169, local binary pattern	Random forest	89.70
2023	Nivyashree and Pramila [32]	CNN	Softmax	80.80
2023	Ghosh <i>et al.</i> [33]	CNN-based two-phase evolutionary framework	Softmax	83.40
2024	Maurya <i>et al.</i> [34]	CNN	XGBoost	87.88
2024	Angelina and Ulfitria [35]	VGG16	Softmax	83.75
	Proposed Method	Resnet50	Optimized Cosine weighted KNN	90.61

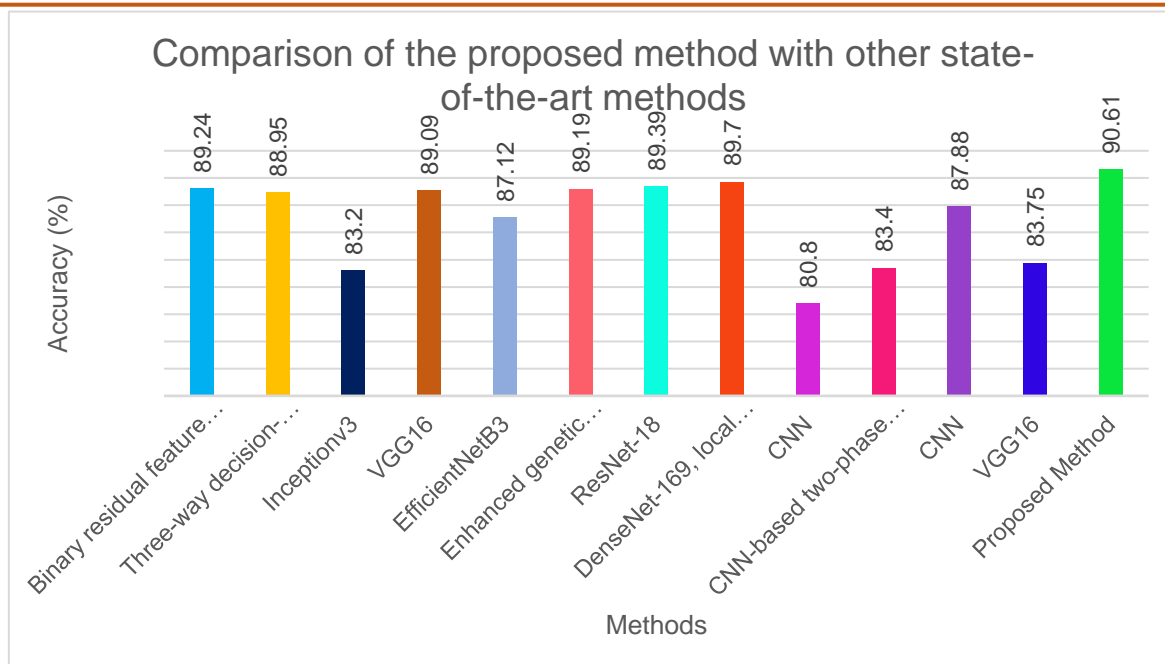


Figure 5. Comparison of the OCWKNN method with other state-of-the-art methods

The proposed OCWKNN model gives high accuracy with good balancing performance between the benign and malignant classes and hence can be appropriate for real-world clinical decision support for early detection of skin cancer.

6. Conclusion

The contribution of this work is a new Optimized Cosine Weighted K-Nearest Neighbor (OCWKNN) model for skin lesion classification, which includes ResNet50 for deep feature extraction, cosine similarity for instance-level weights, and mRMR-based MI score for feature level weights. Besides, the Genetic algorithm has been employed to optimize both instance and feature level weights. Experimental results proved that the proposed approach consistently outperforms other existing state-of-art methods on skin lesion dataset with a classification accuracy of 90.61%. It also achieved the precision of 90.46%, recall of 90.62%, and F1-score of 90.53% with balanced performance across both benign and malignant cases. These results highlight the potential of the proposed OCWKNN method for computer-aided diagnosis systems in dermatology. However, this work only investigates binary classification on one data set. Thus, it may limit the generalization to more multi-class scenarios or for diverse clinical populations. Further modification is needed for OCWKNN with multi-class classification task and its performance on larger and more diverse dermoscopic datasets.

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Authors Contribution Statement

C. Sujdha: Conceptualization, Formal analysis, Investigation, Writing - Original Draft, Software. R. Thirumalai Selvi: Supervision, Software, Writing - Original Draft, Writing - Review & Editing. Both the authors have read and agreed to the published version of the manuscript.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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