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A Metadata-Driven Approach to Malignant Tumor Identification in Dermoscopy Images based on Genetic-Inspired Crow Search Optimized Convolutional Multilayer Perceptron Network

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Introduction: Skin cancer is frequent and deadly thus, early detection enhances patient results. Skin lesions can be magnified using dermoscopy to detect cancerous tumors.
Objective: This paper proposed utilizing an Improved Convolutional Multilayer Perceptron Network (ICMPN) to detect malignant tumors in Dermoscopy Images (DI). Adding lesion features with medical data enhances the model's accessibility and usefulness.
Methods: The suggested model is trained and evaluated by the research using datasets from the ISIC 2019 and ISIC 2020. The preprocessing step focused on noise reduction to enhance image quality, which is critical for accurate analysis. Local Binary Pattern (LBP) separates important sections of images, enhancing feature extraction. Genetic-inspired Crow Search Optimization (GICSO) identified the most dissimilar traits. The approach entails extracting key metadata

characteristics from healthcare records and using this data in the ICMPN architecture training process.
Results: A customized convolutional neural network, the ICMPN, dynamically learns and extracts hierarchical structures from DI to distinguish benign and malignant tumors. Compare the proposed method's accuracy, precision, sensitivity and specificity to evaluate its tumor detection efficacy.
Conclusions: The experimental findings illustrate the model's higher performance in identifying DI, highlighting its potential for clinical applications.

Keywords: Skin Tumor (ST), Dermoscopy Images (DI), Improved Convolutional Multilayer Perceptron Network (ICMPN).

1. Introduction

Skin Tumors (ST) are a very prevalent kind of tumor. As the least prevalent form of STs, malignant is responsible for 85 % of fatalities associated with ST. (1) The most prevalent forms of melanoma of the skin are superficial malignant, Squamous Cell Carcinoma (SCC) and Basal Cell Carcinoma (BCC). Melanoma causes bleeding cutaneous lesions. This skin cancer is the most deadly since it develops in a pigmentation tumor. (2) Ectodermal tissues cover the bones, muscles, tendons and interior organs in seven layers of skin. Human skin contains mesodermal skin cells with melanin discoloration, which can collect UV rays from direct sunlight. (3) Malignant skin tumors are deadly when they spread. Early detection and management improve its prospects. Thus, patchy skin must be diagnosed to protect patients' growth and ensure early medicine delivery. (4) Dermoscopy, a non-invasive skin mapping procedure, is used to detect STs early. Depending on the dermis state, skin tumors can differ visually while moving from dermoscopic to dermoscopic imaging. (5) Dermatoscopy by untrained dermatologists can hinder skin tumor diagnosis. The most crucial thing for dermoscopy is proper training. (6) The ABCD rule identified skin tumors. ABCD stands for Asymmetry, Border, Color and Diameter. Symmetry indicates matching areas, whereas asymmetry means uneven portions. Benign and malignant skin tumors differ. Malignant color balance can include two or more, whereas normal is one. Malignant shapes are wider and broader than normal ones, which are less than half an inch. In difficult conditions, DI is error-prone and requires competence. (7) The variability in dermatologists' malignancy diagnostic accuracy is concerning. The scarcity of competent specialists and high diagnostic prices are major difficulties in medical diagnosis. (8)

The research (9) executed machine learning and image processing techniques to categorize the different forms of STs. During the preprocessing step, dermoscopic images are used as input. The dulled shaver technique is employed for the purpose of eliminating undesired hair fragments from the skin disease. The research (10) indicated the multiple-class skin tumor detection system performed like a dermatologist. Usage for modeling is a previously trained Mobile Network system. The research (11) suggested and tested a novel approach based on a skin cancer classification network using deep learning, with several explicitly accessible data sets as benchmarks. Dermoscopic images obtained from the ISIC archive are utilized in the study (12) to construct a dataset containing two classifications; data can be utilized to categorize both benign and cancerous cancer kinds.

The research [13] offered three novels, unique and effective characteristics for malignancy identification depending on the ABCD rule, together with certain existing characteristics connected to the structure, dimensions and color attributes of DI. The research [14] presented layering models with three layers to classify malignant and harmless skin lesions. The algorithm was honed using 1 000 skin images classified as malignant or harmless. The study [15] introduced a novel automated technique for the detection and classification of skin cancer illness via the analysis of skin images.

- Extraction of Metadata from healthcare records enriches ICMPN design learning.
- Preprocessing with noise reduction improves the image's quality.
- LBP feature extraction for identifying key image areas.
- The research applies an ICMPN on DI to detect early skin cancer.

The research aims to present the following: Methods in section 2, Results in section 3, Research discussion in section 4, Conclusion in section 5.

2. Methods

The study sections depict the subject of "Malignant Tumor Identification in DI," emphasizing the necessity of proper detection in dermatology, where dermoscopy is a non-invasive skin diagnostic method. "Genetic-inspired" approaches can utilize genetic algorithms or evolutionary ideas to optimize identification. CMPN suggests deep learning, especially CNN architecture with a multilayer perceptron, for image analysis. Figure 1 shows the flow of the study's proposed method.

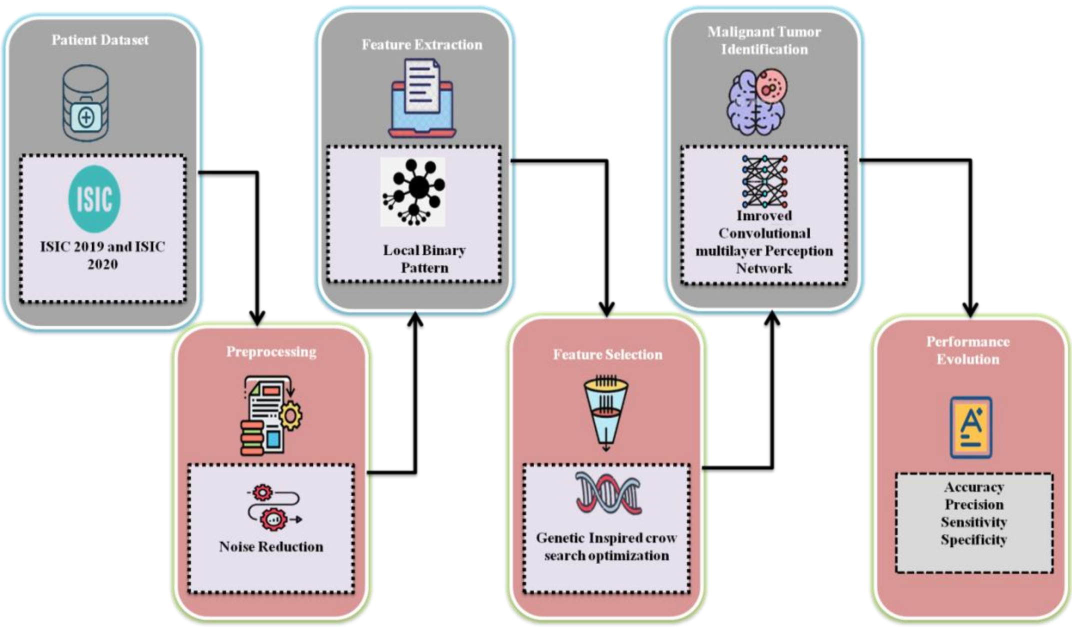


Figure 1. Flow of the Proposed Method [Source: Author]

Dataset

The datasets [16] used in the research 2019 and 2020 was International Standard Industrial Classification (ISIC) data. Database ISIC 2020 comprises 33 465 dermoscopic images taken at several locations for training, which are offered in Digital Imaging and Medical Communications (DICOM) as well as Joint Photographic Experts Group (JPEG) formats, along with metadata. The data comprises client ID, age, sex, basic anatomy, and target value. The training set comprises baseline melanoma and non-melanoma images, whereas the test group has 10 398 relevant drawings. ISIC 2019 contains 245 064 JPEG dermoscopy images. Among the 245 064 dermoscopy images in ISIC 2019, JPEGs are included.

Data Preprocessing Using Noise Reduction

Medicinal images include noise because of poor lighting and air particles. The presence of noise in images causes artifacts. Noise reduction is crucial before any segment or feature extraction method is used. Gaussian kernels are ideal for image smoothing since they reduce noise during acquisition. The kernel coefficients are based on Gaussian's 2-dimensional function.

$$H(b,a) = \frac{1}{\sqrt{2\pi\sigma^2}} f^{-(b^2+a^2)}/2 * \sigma^2 \quad (1)$$

Feature Extraction Using Local Binary Pattern (LBP)

LBP is a way to describe the look of different textures. If a picture pixel compares its color value to those of its neighbors, we can get its LBP code. If the value of the center pixel is higher than that of its neighboring pixel, the LBP bit for that neighboring pixel is set to 0. If it is not, it is set to 1 (equation 2).

$$LBP_{b.k} = \sum_{b=0}^{b-1} 2^b X\, e(s_b - s_v) \quad (2)$$

Skin Tumors Area of Focus Segmentation using LBP

The technique begins with selecting the center point from data points, utilizing an enhanced centroids choice method instead of random centroids. After completing the iteration, the centroid is chosen by taking the mean and setting it as the center position for the following iteration. Repeat until no change is seen in the next cluster center. The K-mean uses the center position selection method in equation (3) to establish its center position.

$$mu = (1{:}L) * \frac{n}{l+1} \quad (3)$$

Feature Selection Using Genetic-Inspired Crow Search Optimization (GICSO)

The sample consists of M crow techniques, with a challenge size of c. At time s, the position of every crow jis represented by a sequence of vectors $r_j^s = [r_{j1}^s, r_{j2}^s, \dots., r_{jc}^s]$for $j = 1,2,3, \dots, M$, when r_j^s feasible dimension-based positioning method of c for crow j. if the j crow wants to take something from other crows i, two scenarios can arise: If crow i does not monitor crow j, crow j will identify crow i 's pantry and maintain its location (equation 4).

$$r_j^{(s+1)} = r_j^{(s)} + q_j * fl_i^{(s)} * \left(n_i^{(s)} - r_i^{(s)}\right) . \tag{4}$$

When f is the flying distance, let q_j be an integer at random that $\in$ between 0 and 1. Crow i wanders wildly to deceive crowj. The two examples can be joined scientifically:

$$r_j^{(s+1)} = \begin{bmatrix} q_j^{(s)} + q_i * fl_i^{(s)} * \left(n_i^{(s)} - q_j^{(s)}\right), q_i \geq AP_j^s \\ \text{Choose b random position} \qquad \text{Otherwise} \end{bmatrix} \tag{5}$$

When q_j and $q_i$are some numbers that $\in [0,1]$and AP_j^s is the comprehension rate for crow, furthermore i at t repetition is j. Crows' seeking abilities are influenced by $fl.fl$ levels. Once an accurate value is determined, the crows adjust their places. The feasibility of every upgrade is checked. Crow recollections are refreshed by (equation 6).

$$n_j^{(s+1)} = \begin{bmatrix} r_j^{(s+1)} \text{ if } e\left(r_j^{(s+1)}\right) \text{is better } e\ (r_j^{(s)}) \\ n_j^{(s)}, \text{ otherwie} \end{bmatrix} \qquad 6)$$

Improved Convolutional Multilayer Perceptron Network (ICMPN)

An ICMPN includes convolutional layers for gathering features and fully connected units for classifying or analysis. This hybrid design excels in picture identification, classification and optical data analysis. Figure 2 shows the flowchart of ICMPN.

Convolutional Neural Network (CNN)

CNN are deep learning models that analyze structured grid data like images and videos. It excels in picture identification, object detection and segmentation. CNNs resemble the human visual brain and dynamically develop structure-based feature representations from unprocessed data.

Convolutional operation

Convolution extracts characteristics from input data via filtering. For a certain point (i, j) in the feature track, the method of convolution is expressed as:

$$K(i, j) = (V * L)(i, j) = \sum_n \sum_m V(i + n, j + m) \times L(n, m) \tag{7}$$

$K(i, j)$Shows the value of the final attribute map at that position(i, j). Vis the input picture or feature diagram. L is the convolutional kernel or filter.

Functional Activity

The functional activity brings irregularities into the system. Rectified Linear Unit (ReLU) is a popular activating function for CNNs and it can be defined as:

$$e(w) = \max\ (0, w) \tag{8}$$

Mechanism of Pooling

The most frequent pooling operation is a pooling method when the greatest entity to the attribute mapping region that the criteria covers is selected. The equation for maximum pooling is as follows:

$$K(i,j) = \max(V(i,j)) \tag{9}$$

$K(i,j)$ Is the dimension of the resultant map of features at location (i,j) and $V(i,j)$ is the value of the source feature mapping.

$$O = X.W + a \tag{10}$$

Here, O is the output vector, W is the contribution vector, X is the power medium and b is the distorted tensor. These equations describe the basic processes of a CNN.

Multi-Layer Perceptron (MLP)

MLP is a feed-forward synthetic neural system with several layers, including one for input, one or more hidden layers and an output layer. Here are the equations that reflect the essential operations in a simple MLP:

Weighted summing at buried layer neurons

Computing the weighted cumulative inputs at each hidden layer neuron:

$$Y_i = \sum i = 1n(x_{j,i} * W_j) + a_i \tag{11}$$

The entire input to the activation role of the j^{th} of the secret layer neuronal is denoted by Y_i. The weight associated with the link between the i^{th} input and the j^{th} neuron is denoted by $x_{j,i}$. The value of the i^{th} input is represented byW_j. The bias associated with the j^{th} neuron is denoted bya_i.

Functional activity

The functional activity brings non-linearities into the network. In MLPs, common activation functions include the sigmoid tangent hyperbola and the "rectified linear unit." The sigmoid activation role is represented as follows:

$$e(Y) = \frac{1}{1+f^{-y}} \tag{12}$$

The functional activity for tangent hyperbola (tanh) is:

$$e(Y) = \frac{f^y - f-^y}{f^y + f-^y} \tag{13}$$

The functional activity of the Rectified Linear Unit (ReLU) is:

$$e(Y) = \max(0, Y) \tag{14}$$

The overall weight at each output layer neuron

The weighted sum of the inputs at each neuron in the output layer is determined as follows:

$$Z_l = \sum_{i=1}^{n}(\omega_{il}^{s} * e(Y_i)) + a_l' \tag{15}$$

The entire input to the k^{th} neuronal in the production layer is denoted by Z_l. The volume corresponding to the link between the j^{th} neuronal in the final hidden layer and the k^{th} neuronal in the production layer is denoted by ω_{il}^{s}. $e(Y_i)$ is the outputs of the jth neuron activation function in the last hidden layer. The bias associated with the k^{th} neuronal in the production layer is denoted through a_l'.

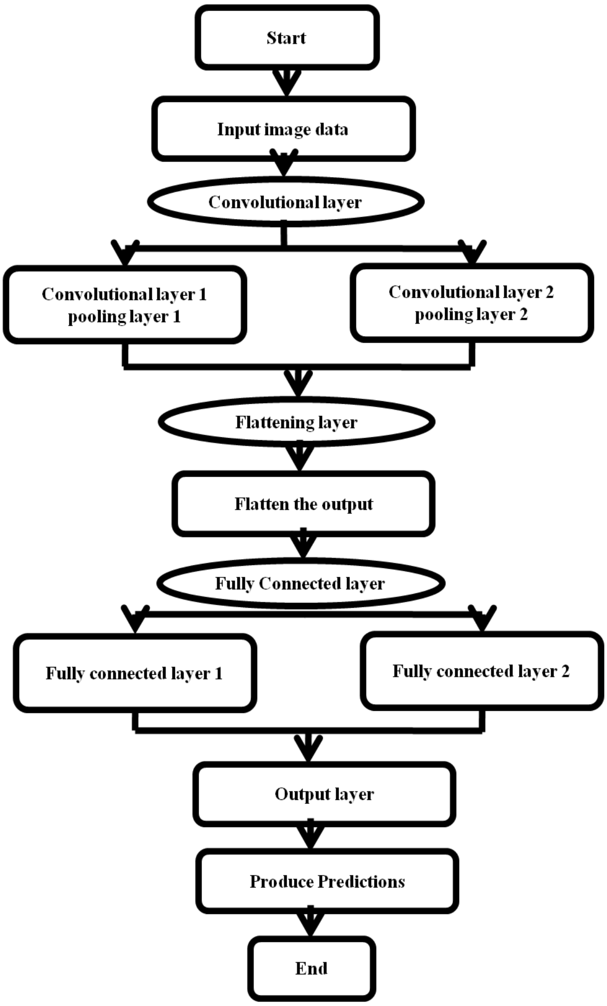


Figure 2. Flowchart of ICMPN [Source: Author]

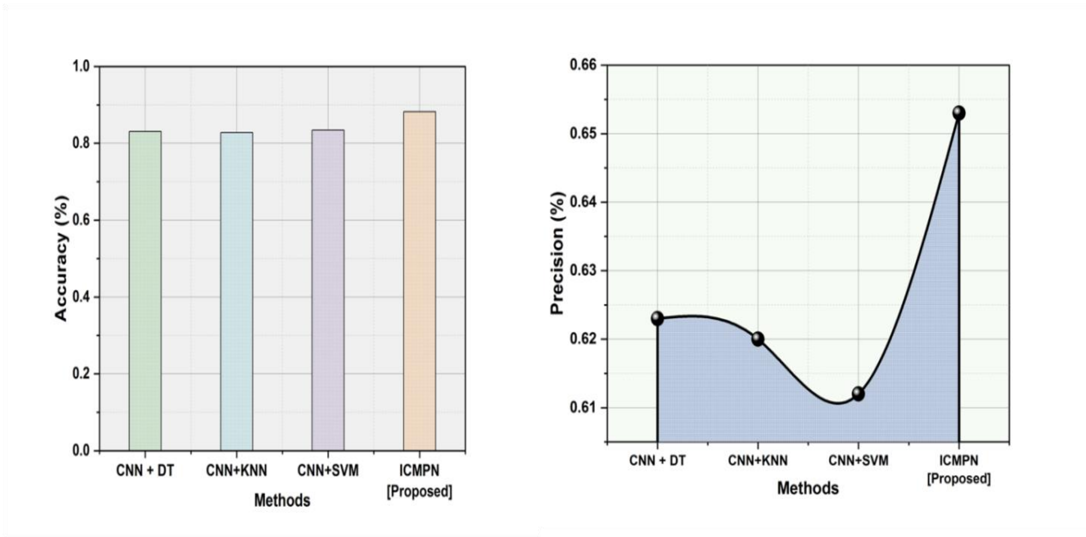
3. Results

Windows 10 edition with Pytorch 1,0, compliant with Python 2,10, is part of the system setup. We used Python 2,10 for our method. Featuring a Radeon RX 7900 XTX GPU and Ryzen 7 5800a X CPU, the hardware can perform demanding AI workloads. This section presents the malignant identification through dermoscopy images. Our novel approach, ICMPN, is used to assess the existing approaches including Convlotional Neural Network + Decision Tree (CNN+DT) [17], Convlotional Neural Network + K-nearest neighbor (CNN+KNN) [17]and Convlotional Neural Network + Support Vector Machine (CNN+SVM) [17]. Accuracy, precision, sensitivity and specificity belong to the measurement factors. Table 1 demonstrates the outcomes of existing and proposed methodologies.

Table 1. Reset of Existing Approaches [Source: Author]

Methods	Precision (%)	Accuracy (%)	Specificity (%)	Sensitivity (%)
CNN+SVM	0,612	0,834	0,944	0,387
CNN+KNN	0,62	0,828	0,921	0,453
CNN + DT	0,623	0,831	0,924	0,453
ICMPN [Proposed]	0,653	0,882	0,997	0,476

Accuracy is used to measure how accurate a model's results are as a whole. A model's precision is a measure of the way that it makes exact good predictions. Figure 3 (a) and (b) examined the result of accuracy and precision values. ICMPN had the highest accuracy and precision scores of 0,882 % and 0,653 % compared to CNN+DT, CNN+KNN and CNN+SVM.



(a) (b)

Figure 3. Outcomes of (a) Accuracy and (b) Precision [Source: Author]

Sensitivity measures whether a model can identify true beneficial occurrences from others. Specificity evaluates the ability to detect bad occurrences among the real ones. Figure 4 (a) and (b) illustrate the result of sensitivity and specificity. Table 1 indicates the outcomes of the sensitivity and specificity values. ICMPN had the greatest sensitivity and specificity scores of 0,476 % and 0,997 % compared to CNN+DT, CNN+KNN and CNN+SVM.

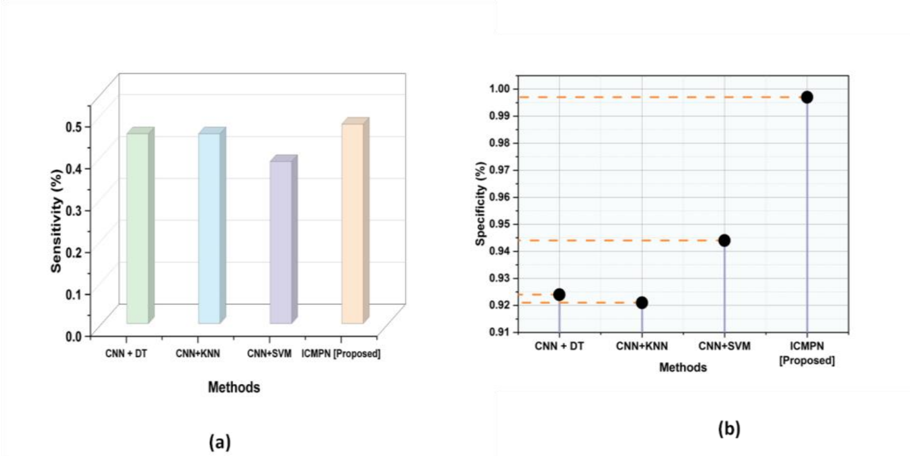


Figure 4. The outcome of (a) Sensitivity and (b) Specificity [Source: Author]

4. Discussion

The existing approaches CNN+DT, CNN+KNN and CNN+SVM have some limitations like increase the risk of over fitting to the training data, the combined model might be challenging to interpret, especially in complex decision-making scenarios. This can increase processing time and resource needs, restricting its use in real-time clinical situations. The large and varied dataset is required to capture dermoscopy image variances of the model. Quality and resolution of dermoscopy images could impact model performance, Actual illumination and device differences can alter image quality and model reliability, as well as a mixed model can need compliance with regulation, system connectivity and medical staff usefulness in clinics. To tackle the difficulties discussed above address the suggested ICMPN methodology.

5. Conclusion

Early skin cancer identification can boost therapy for a common and dangerous condition that uses dermoscopy to increase skin tumors. Because of its incidence and fatality, early skin tumor detection is crucial for the health of patients, the research found. The paper introduces a dermoscopy-based ICMPN for malignant tumor detection. The study found that our proposed technique, ICMPN, experiences the greatest accuracy, precision, sensitivity as well as specificity of 0,882 %, 0,653 %, 0,476 % and 0,997 %. Further research has the potential to enhance skin and demographic diversity in the field of skincare and other personal care goods. The enhancement of hardware optimization and the integration of real-time implementation have the potential to enhance the clinical utilization of the technology.

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