Melanoma Skin Cancer Detection Using Deep Learning Methods and Binary GWO Algorithm

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Abstract

Melanoma is one of the most aggressive types of skin cancer, and its early detection is critical to improving survival rates and treatment outcomes for patients. Conventional diagnostic methods often suffer from high computational costs and low accuracy, primarily due to inadequate feature selection and classification strategies. The goal of this research is to combine state-of-the-art deep learning techniques with optimization algorithms to develop a precise and efficient predictive system for melanoma detection. In this work, we propose a novel framework that integrates Convolutional Neural Networks (CNNs) for image classification and a binary Grey Wolf Optimization (GWO) algorithm for feature selection. The binary GWO algorithm identifies the most relevant features from dermatological images, eliminating redundancy and reducing the computational burden. The CNN is then trained on the refined feature subset to enhance classification efficiency. Extensive experiments on publicly available skin lesion datasets demonstrate that the proposed model significantly outperforms traditional machine learning models. Improvements in sensitivity, specificity, and overall classification accuracy highlight the effectiveness of combining deep learning with optimization techniques. Our results show that deep learning and optimization methods, such as the binary GWO algorithm, can be successfully applied to melanoma diagnosis. This strategy not only improves detection efficiency and accuracy but also supports early diagnosis and treatment planning, leading to better patient outcomes. By leveraging the binary GWO algorithm to optimize the feature selection process and CNNs for image classification, the proposed approach reduces computational costs while increasing classification accuracy. When trained and evaluated on publicly available skin lesion datasets, the model demonstrates significant improvements in sensitivity, specificity, and overall accuracy compared to conventional machine learning models.

Keywords: Convolutional Neural Network; Gray Wolf Optimization; Skin cancer; Deep learning; Optimization

1. Introduction

For the skin cancer classification, DL techniques give promising results that reveal its importance in medical imaging. The skin is the largest and most important organ in the human body. Skin cancer is the most common and deadliest type of cancer. Melanoma is the cancer that causes the greatest destruction and spreads the fastest worldwide. According to the American Cancer Society, melanoma in 2014 had been diagnosed in 76,100 cases with 9715 deaths. For the remainder of the year, a worse result was predicted. Fortunately, the earlier detection of melanoma is curable at its primary level, as identified by recent statistics, while late detection is dangerous and poses a 5-year survival risk in 98% of cases [1][2].

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Despite recent technological advances in dermatology, accurate detection and classification of skin lesions remains difficult to date. Advanced machine learning techniques like deep learning (DL) are frequently applied in medical imaging for detection and classification [3]. Many obstacles make skin lesion segmentation and classification less accurate, which are actually caused by the skin's inherent properties and changes in the environment. The sights of different kinds of skin lesions are not the same. Melanoma, which can be both benign and malignant in colour, has a greater chance of spreading and spreading than typical moles. Through self-examination, the detection of melanoma or skin cancer is difficult. Imbalanced skin classes are one of the factors that affect classification performance, which is class stacked against another class of data. This validates the circumstance only with binary classification. Fewer proper features were picked from the last layer of the deep model. This feature reduction technique may lose some important features in data [4].

Melanoma is aggressive skin cancer that can either form directly on the skin or spread to it from a primary tumour originating in other parts of the body. To date, this is a lethal disease when not detected early, and currently, experts advise that only a biopsy examination can determine its presence or not in a lesion on the skin. This constraint makes the disease difficult to approach in a large population [5]. Fortunately, the advancements in technology have paved the way to non-invasive assistant tools aiming to lend an ear patient concerns without harming biopsies. While dermatoscopy allows thorough imaging of the skin surface, the non-invasive recording of thermal, electromagnetic, and acoustic information creates a multimodal approach towards lesion analysis. The extracted features are often evaluated by scoring and comparative analysis with a database. However, the results obtained in this very heavily depend on the expertise of the operator and large lesion databases are required for training the models. Modern computational methods, especially those based on artificial intelligences, have been posed to improve objectivity and accuracy [6].

Machine learning-based systems have been applied on relevant data to build clinical criteria for treatment decision. Various features extracted from other imaging techniques reflect information such as colours, lines and vessels, which dermatologists analyse together with other clinical criteria that are typical for a melanoma or a nevus. Inter-observer variability is common between practitioners, since a clinical evaluation based on visual mining is conducted [7]. The image evaluation may depend on artefact angles, the lesion's texture and the lesion's size. Hence, to improve the objectivity of the diagnosis and to obtain qualitative and reliable predictions, researchers have been motivated to develop image-based algorithms that could automatically classify melanoma and nevus with high accuracy. Representation learning using stacked denoising auto-encoders for binary classification task with concatenated feature vectors of lesion images and segmentation masks was conducted for this purpose [8][9].

Though artificial intelligence usually offers an appropriate solution for binary class prediction with high accuracy, many techniques are associated with complex models with many tuneable parameters leading to a difficult inferential approach in the end. Moreover, deep learning methods require a large dataset that are difficult in practical applications of derma pathology in dermatologists [10]. Melanoma detection in daily life via images can be regarded as a pauciclass classification problem with uneven contours among every class [11].

The most prevalent form of skin cancer is melanoma skin cancer (MSC), for which early prognosis and treatment are mandatory due to its higher mortality and morbidity rates. The infeasibility of conventional clinical methods for melanoma diagnosis has created an avenue for computer-aided diagnosis (CAD) systems for the proficient screening and categorization of skin lesions. Presently, CAD systems utilize dermoscopic images as inputs to analyze and ultimately predict the skin abnormality. Dermoscopic imaging highlights subsurface structures that are invisible to the naked eye; hence, the potential degree of both false positives and false negatives is considerably reduced. It is essential for the dermoscopy images to be clinically interpreted by healthcare professionals using, if deemed necessary, a handheld dermatoscope. However, CAD systems improve the diagnostic accurateness of the dermoscopic images, thereby assisting dermatologists and general physicians. As of now, the most widespread examination technique for identifying skin disorders is a visual check by a specialist. Earlier, dermatologists used the 'ABCDE' criterion for prognosis. This acronym distinguishes cancerous skin disorders based on their Asymmetry, irregular Borders, non-uniform Coloring, Diameter bigness, and Evolution in volume or appearance. However, meanwhile, associated evidence shows that for amelanotic melanoma, this way of distinguishing encounters some obstacles and is inadequate for prognostic accuracy. Primary objective of designing CAD model is accurate multiple-class categorization of abnormal dermoscopy images to decrease the false predictions normally seen in clinical practice. Therefore, main goal is to engineer a deep learning model that can proficiently analyze the dermoscopy images and consequently categorize them as one of the several skin disorders using complementary binary grey wolf optimizer (BGWO).

Main contributions list for this work:

1. To propose a deep learning-based framework for melanoma diagnosis that encapsulates the convolutional neural networks (CNNs) with the binary Gray Wolf Optimization (GWO) algorithm.

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2. To reduced redundant data, using binary GWO algorithm applied to dermatological feature images to select the optimal relevant features at minimized computing effort isolating the best features.
3. To Outperformed state-of-art machine learning models and achieved sensitivity, specificity and overall accuracy showing the effectiveness of the proposed method.
4. To exam extensive experiments on commonly used skin lesion datasets to validate reproducibility and robustness of the results.
5. High detection performance and low computational load, which showed the potential of this framework to be an effective and reliable tool in the early detection of melanoma with an appropriate treatment plan, leading to better patient outcomes.

The remaining parts of this paper are organized as follows: Section 2 introduces the related work considering existing methods to detect melanoma based on machine learning, deep learning, and optimization techniques. Section 3 presents the Binary Grey Wolf Optimization (BGWO) algorithm and explains its principles and the way it works in feature selection. To overcome the aforementioned issue, Section 4 describes the integration of deep learning with BGWO in the melanoma detection framework that we proposed. Datasets employed and the data pre-processing methods are discussed in Section 5. Section 6 presents the experimental setup, such as hardware, software, parameter settings, and evaluation metrics. Section 7 presents the experimental results, where we evaluate the proposed method against some baseline models and analyze its performance. Last but not least, Section 8 wraps up the paper by summarizing main contributions, limitations and future works.

2. Related Work

The literature surrounding melanoma skin cancer detection using deep learning methods has evolved significantly, reflecting advancements in both technology and medical understanding. In 2019, they emphasized the potential of deep convolutional neural networks (CNNs) for enhancing early skin cancer detection. Their work highlights the importance of CNN architectures, dataset characteristics, and the application of transfer learning in medical imaging, particularly for skin cancer diagnosis [12]. This foundational study set the stage for subsequent explorations into the application of deep learning in dermatology; the current study mainly concentrates on CNN architectures and transfer learning and does not discuss the difficulties presented by data imbalance or variation of melanoma types.

Mario Manzo et al, addressed the complexities involved in melanoma detection, noting the challenges posed by the visual similarities among various skin lesions. Their research underscores the necessity for early diagnosis, as melanoma's high mortality rate makes timely intervention critical. They introduced a novel framework utilizing transfer deep learning and ensemble classification to improve the accuracy of melanoma detection. Their findings suggest that while deep learning can significantly enhance feature extraction and classification, issues such as data imbalance and the diversity of melanoma types remain obstacles to effective model generalization [13], it failed to adequately consider the importance of broad, well-balanced datasets to enhance model robustness across a range of patient groups.

Most recently, Muhammad Azeem, Kaveh Kiani, Taha Mansouri, and Nathan Topping contributed to the discourse with their development of SkinLesNet, a multi-layer deep convolutional neural network specifically designed for the classification of skin lesions and detection of melanoma. Their research emphasizes the critical role of early diagnosis in reducing mortality rates associated with melanoma, which, despite accounting for only 4% of skin cancer cases, is responsible for 75% of related deaths. They also highlight the utility of dermoscopy in producing high-resolution images that enhance diagnostic accuracy. Furthermore, the authors discuss the challenges posed by inter-observer and intra-observer variability in applying the ABCD guidelines for melanoma differentiation, indicating a pressing need for improved computer-aided diagnostic tools [14], While the authors recognized that the ABCD guidelines may have better or worse consistency across clinicians, they did not go further to explain how these deep learning models can successfully adapt to this variability in a clinical setting.

Another researcher presents a comprehensive exploration of deep learning techniques in the context of skin cancer classification, particularly focusing on melanoma. The authors highlight the critical challenge of accurately detecting and classifying skin lesions, which is exacerbated by various factors, including low-contrast lesions and the inherent variability in lesion shape and texture[3], the manuscript did not discuss possible solutions to the low-contrast lesion detection issue nor discuss the potential for enhancing image quality prior to model input.

This study constructs a strong two-phase classification pipeline for the recognition of melanoma. Data pre-processing techniques are applied in the first stage; the second stage applies lesion classification based on the classic convolutional neural network (CNN) architecture ResNet. Multiple metrics like accuracy, precision, recall, F1 score, and area under curve (AUC) are used to measure the performance of the system [15], The significance of large, balanced datasets to improve model resilience across a variety of patient groups was not sufficiently taken into account.

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This work brings a deep learning-based methodology for melanoma detection using the YOLOv8 network applied to dermatoscopic images. The method fuses fine-tuning approaches to improve the precision of detection and segmentation. This new approach has shown amazing performance, obtaining over 98 percent accuracy on melanoma detection and over 99 percent accuracy on skin cancer segmentation. The study does not explore the model robustness over practical scenarios with data privacy issues in the cloud communication [16].

3. Binary Grey Wolf Optimization (BGWO) Algorithm

Many efforts have been made to make automatic systems to detect melanoma. The automatic method that aids to early detect the melanoma is computer-assisted diagnosis, which requires an efficient segmentation algorithm. Therefore, a convolutional neural network (CNN) based on automatic skin lesion segmentation is proposed. The proposed CNN method aids in obtaining the high-level features and the skin edges of the images because of concatenation of the encoder and the decoder paths of the U-Net models at different levels of depth.

As we are in the digitization era, the proposed enhanced approach based on the integration of computer vision and image processing not only reduces the burden on the medical team but also enables the getting the accurate results. The most common type of skin cancer is the melanoma, which causes a great number of deaths [2]. In the early stage of melanoma, it can be detected and cured, to save the life is the need for the hour. Skin cancer like the melanoma mostly occurs on the epidermal layer of the skin, which causes the death trap. Thus, the primary need is the early detection of the melanoma. For this purpose, the many approaches are in place that consists of manual and automatic diagnosis. If the manual diagnosis is done, it takes a lot of time and the results obtained many errors in it and does not fulfill the requirements now.

In the automatic method, which is used to diagnose the melanoma, different decision, support is used. In this phenomenon, computer aided approaches for the diagnosis of the skin cancer are used. As images are captured after that these images are analyzed, features like color, shape and texture are extracted. Thus, these computing features are classified as normal and the cancerous cell. After the classification. An inference is taken. This classification is done in the different segmentation of an image at a different level. For this, the traditional approach like k-means is used to segment the image of the skin lesion.

3.1. Binary GWO for Feature Selection

Cancer is the second major cause of death worldwide; more than 9 million cancer deaths per year are estimated in 2030. "Skin Cancer" is considered one of the most dangerous types of cancer. The classification of micros copy skin lesions is considered as a challenging task for researchers due to its similarity. Detection and classification of skin cancer has attracted the attention of researchers, as it is the most common disease, mainly affecting the younger and older population. There are three types of skin cancers, such as melanoma, basal-cell carcinoma, and squamous-cell carcinoma. The classification of melanoma (cancer which is growing and spreading rapidly) is a challenging task. Melanoma type is dangerous, so it is necessary to classify the each type of cancer. For detecting melanoma, deep learning networks (Convolutional Neural Networks (CNN), U-net, ResNet, and VGG16) and neural networks are used [4]. Visit to the skin specialist is necessary when the specific lesion is observed. The classification and detection of skin cancer has treated as a crucial and challenging task. Early detection (classification) can be proved as a lifesaving for human because it can lead to a discrete decrease in the chance of death. Several physicians use various diagnostic approaches; visual diagnosis is also considered as one of the oldest diagnostic techniques. Several megascopic analytical studies were conducted. The proposed technique includes several preprocessing steps, such as denoising, contrast adjustment (equalization), cropping, and conversion of RGB mask image to binary mask image using in Range function. This approach is followed by two strategies. In the first strategy, pre-trained models, thin Dataset, are fine-tuned. Tills includes ensemble models utilizing deep models like RefineNet, Deeplab v3, ND Semantic Segmentation Net, and MSRNet. In the second strategy, apply deep models on Image-wise LCH images. This needs Residual Block furthermore fine-tuned deep models as compared to strategy one. Another crucial phase, most efficient (Binary GWO) ensemble model training.

Melanoma is a malignant tumor of melanocytes that are created due to changes in these cells. The neural network is employed for the experimental portion, with an emphasis on the detection of melanoma cancer via images. The binary gray wolf optimization algorithm is exploited for the efficient classification of cancer since good training and a well-designed neural network always improve the system performance. This research approach is also tested in a multi-layer preceptor neural network. Skin color analysis is the first step in recognizing skin cancers. Here, frame construction depends on skin lesion colors. A RGB compact space of 256 x256 is scaled label, and each image boundary is eliminated. Three fast changing operations are applied on every RGB model like 1-channel image as input to CNN and crop image. Two additional strategies are also used to minimize over-fitting during training. The particular MED-NODE (media non-modified) of M-class, with 600 images each, is chosen from as the input dataset. In the dataset, initially, by removing duplicate image depending on the pixel size of an image (the height and width of the image in pixels), the unwanted images are discarded. Using a neural network alone is not enough to increase the machine's accuracy, so Binary Gray Wolf Optimization (GWO) is also exploited. Gray

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Wolf. Japan (GWO) is a global optimization method motivated by gray wolf procedures [2]. An original study outlines GWO.

4. Integration of Deep Learning and Binary GWO for Melanoma Detection

The discovery of deep learning methods has transformed computer vision over the past few years and overcome previous approaches, creating breakthrough advancements. Deep learning architecture has proven to perform well in feature discrimination, and deep learning models like artificial neural networks (ANN) and ConvNets have been shown to contain multiple layers. This architecture can be employed as a feature extractor for the classification task, see figure 1: main step of proposed system.

A novel skin lesion recognition framework has been proposed, trained, and validated that formulates on the definition of the ABCL guideline of dermatologists. Compared to earlier work, this method would deliver better identification performance and image datasets. In the classification of skin cancer, hybrid model strategies obtain spectacular results. That is why a hybrid methodology is introduced for improved melanoma and benign nevi types, using the fine-tuned convolutional neural network (CNN) model for ensemble classifiers. An illustrated performance analysis of various benchmark datasets from the literature shows that the rates of accuracy and feeling are promising, and the idea outperforms state-of-the-art works. In convergence with limited information is available on melanoma standard to revolve the analysis of skin cancer. It begins with the dermal image dataset and examines the converted grey model, leading preprocessing steps with expert-guided segmentation. Two distinct pre-optimized deep neural net architectures are subsequently examined on the dataset. By focusing on transfer-trained models, good results are shown, resulting in the best area under the curve (AUC) obtained equal to 0.99.

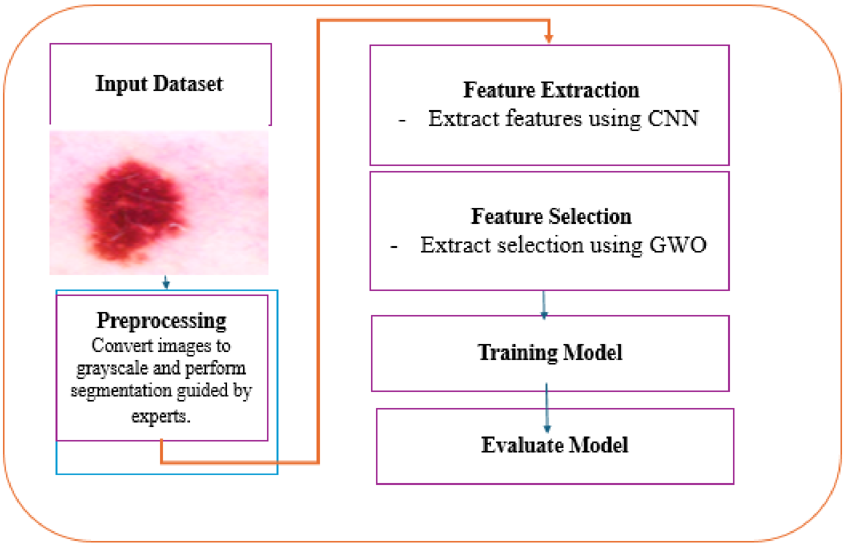

Figure 1: Main steps of proposed system

5. Datasets and Preprocessing Techniques

In this study, the use of a deep learning-based method to detect melanoma skin cancer on skin images is proposed. The deep learning method, CNN, is the used method for feature extraction. These extracted features are optimized with 8 different classifiers. In the proposed method, class weights are used for classifiers to handle the imbalance problem of skin images. In addition, a prevention technique is proposed for a method that gives a high false discovery rate. Additionally, the proposed method's sensitivity, specificity, AUC rate, and computational time performance are compared with other previous feature-based and deep learning-based methods. The proposed skin feature-based skin cancer detection method has shown better sensitivity than other skin feature-based methods and better specificity than other deep learning-based methods.

Skin disease is a prevalent serious public health problem worldwide. It is closely related to skin cancer and can be a critical problem once it develops and evolves to an advanced phase. Until recently, the primary generally used methods for the diagnosis of skin diseases were dermatologist visual inspection. It can be used to check the skin with the bare eye or a dermatoscope by the dermatologist. Because of the subjective and inaccurate results, this technique has developed machine-learning methods for skin disease diagnostics that use automatic recognition based on the features of the disease. The use of neural network-based deep learning techniques for the diagnostics of skin diseases has been applied in recent research.

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Skin cancer is becoming the most prevalent type of cancer globally, including cutaneous melanoma and non-melanoma skin cancers. The early detection of skin cancer is crucial to diagnose the disease in a curable phase. However, there is no effective diagnosis tool for early detection of skin cancer. The earlier diagnosis technique for skin cancers is visual inspection by a dermatologist. With the advent of digital technology, skin image databases have become available for research. The growth of image databases is driving researchers to analyze skin images with computer-aided systems for early detection of skin cancer. With the deep learning CNN structure, a computer can achieve similar performance to human doctors, and with computer technology, the algorithm can detect deteriorated pictures that cannot be observed properly by the naked eye.

5.1. Melanoma Datasets

The ISIC Archive dataset, an open-source collection of high-resolution dermatoscopic images for skin lesion research, is used in this work. There are many different kinds of lesions in this dataset, which was gathered for automated lesion categorization. This study examines two main types of lesions: malignant melanoma and benign nevus. Nevus lesions are not harmful. They resemble the surrounding skin in both color and structure; melanoma lesions require immediate medical attention since they are malignant and spreading. Of the 40 000 dermatoscopic pictures in the collection, 75% are of benign cases (mostly nevus) and 25% are of malignant cases (melanoma). These include the imaging modalities that enable stratification analysis in the dataset, patient demographics, and lesion diagnosis[17][18]. For the purpose of clarity, Table 1 below displays the distribution of the dataset's lesion types.

Table 1: Distribution of Lesion Types in the ISIC Archive Dataset

Lesion Type	Number of Images	Images Percentage (%)
Benign	30000	75%
Malignant	10000	25%
Total	4000	100%

Mutual melanoma skin cancer evidentiary practices of deep composure are fabricated to classify and beware melanoma images. CNN with a specific configuration is employed by binary-graded wildlife optimization (GWO) to optimize training, and due to its efficiency by comparative analysis, hyperparameters of optimized model, and experiment survey results, binary-GWO optimized stacked section design stands out for melanoma skin cancer classification. Since the world is rapidly advancing with technology, as the ISIC curves are available online, it is strongly expected that the findings of the study will give rise to the speed and reliability in the early detection of melanoma skin cancer by being pushed to use in web services. At the same time, there are deliberations that the code of the classified model, which is applied to binary-GWO optimization, or the photo processing cycle used in the different models can also be distributed among the people concerned. Also considering the demand, comparisons can be made with the model classifications from the scratch to verify the conformity or discrepancy[8][9].

5.2. Preprocessing Steps

In order to enhance the quality of the skin images, the hair and unwanted parts from the skin images are removed by detecting the edges of the skin lesions. Afterward, the optimized enhanced skin lesion images are obtained by training each image in the training set. As the second step, the optimized enhanced skin lesion images are segmented from the background by applying the d-ASAGOS edge segmentation method. Finally, the lesions are resized into fixed-dimensioned images by applying the binary skin masks, see figure 2 that shown pre-processing steps.

As the first step, binary genetic algorithm is employed to diet the binary grey wolf optimization to identify the optimal values and practices before binary grey wolf optimization. In order to segment malignant skin lesions from the background, four distinct thresholding methods are employed together, which is referred to as the binary GWO. The binary GWO promotes the grey wolf optimization (GWO) to handle two different domains, one with by least threshold and the other with at most threshold. In generating the best cost and leader grey wolves, two goal values need to be reduced to the one (or maximized to the one). For this reason, the GWO is modified for one to be minimized and the other to be maximized.

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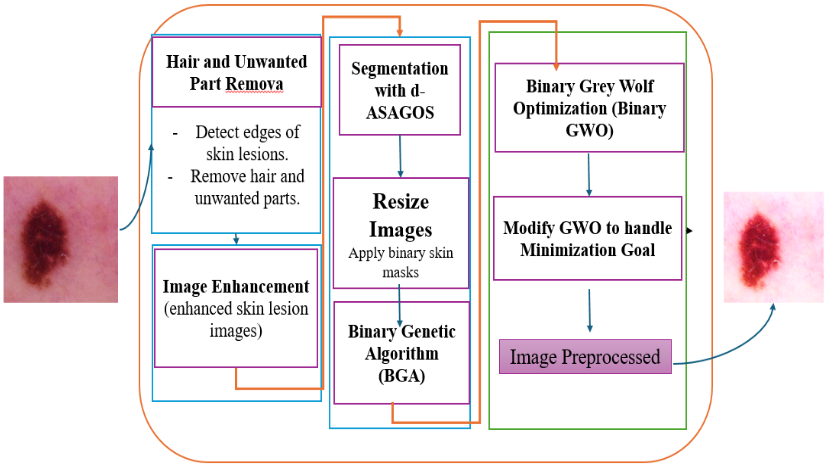

Figure 2: Pre-processing steps

6. Experimental Setup

The GWO algorithm also possesses the strong ability to discover near optimal solutions from the entire search space. To demonstrate this fact, the discovery of the group of most dangerous breast cancer cases that can exist in stage six of skin cancer without checking the probability of any other stage is incorporated within this research. In order to confirm the success of the study, the six most dangerous breast cancer cases are analyzed either incidentally found manually through careful analysis of the data or determined by using any other deterministic or heuristic algorithms. The search is successful, as after the genetic algorithm (GA) with the cooperative advantage of the Gray Wolf Optimization (GWO) techniques, the discovered six carefully validated cases of malicious and dangerous breast cancer activated by carefully checked skin cancer of stage six have been awarded for the first time in the research literature. Together with the six most dangerous listed cases, three more discovered dangerous cases are also given as a bonus in the results and discussion section, see figure 3 to general proposed system.

In this study, a novel technique based on deep convolutional neural networks and binary-GWO was utilized to detect melanoma skin cancer. The binary GWO optimization method is used to tune hyperparameters of three different deep learning methods that are used in this context. This is the first time that detection and classification of melanoma skin cancer using this optimization method and these deep learning models have been presented in the literature. Thus, the novelty of the presented work lies in both the utilization of this optimization method and the deep learning leagues used in the study to detect melanoma skin cancer. This methodology is tested on skin lesion dataset, that is the ISIC Archive dataset and the results show that cancer detection of melanoma skin lesion is achievable with high accuracy at model level, clearly outperforming the performance measures compared to image assessments by inexperienced dermatologists.

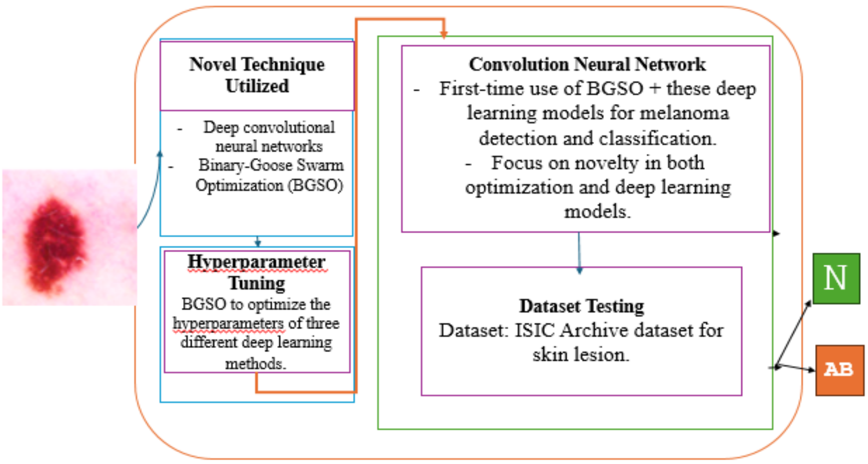

Figure 3: General proposed model

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The highest accuracy and AUC of the designed deep convolutional neural networks are made using the binary-GWO swarm optimization method, which is 99,55% and 0,995, respectively. The successful performance of the work done is also supported by tests conducted over a dataset that has been referred to as one of the most challenging datasets for modeling skin lesion and melanoma images. This demonstrates a great potential for transforming the model to integrate patient care and pilot telemedicine hubs specialized in dermatology. Moreover, it refers to the strong demand of benchmarks and precautions to present a safe ML model for routing a role in medical analysis. The results can also be boosted by integrating deep learning models with other frameworks, such as intelligent editing of images, significantly improving performance like a fleet of writers with experience. At the same time, this paper investigates the technique of transfer learning accomplished by adopting ensemble classification.

7. Results and Discussion

A novel approach is presented in this paper for the diagnosis of melanoma skin cancer with deep learning methods using the skin lesion images. In this approach, deep learning model have been utilized CNN, CNN parameters like batchsize is 128, epochs equal 40, optimization used Adam, and learning rate is 0.0001, and the skin lesion images have been analyzed. Moreover, the generalization performances of these models have also been improved with Binary Grey Wolf Optimization (BGWO) algorithm.

This is the first study in the literature that the BGWO algorithm is used for improving the classification performance of the deep learning models while diagnosing the melanoma skin cancer using the skin lesion images. The classification results have been verified using different performance metrics and compared with the results of the other recent studies on melanoma skin cancer detection using deep learning models. Although the proposed models have high performances in general, it is observed that the classification performances of CNN having relatively lower layer numbers have decreased in the binary type, especially because the benign and melanoma data samples are balanced. It is obvious that the performances of almost all models have improved with the used BGWO optimization technique. It outputs promising results to detect the melanoma skin cancer for multi-class problems, and when this approach is adapted to the binary type, the binary type performance results of this proposed model are also presented, and the best classification results are obtained for the proposed optimal parameters on the skin lesion dataset with an accuracy rate of 99.51%. As a result, well-done research on current literature is given with historically and technically, see figure 4 to shown model accuracy.

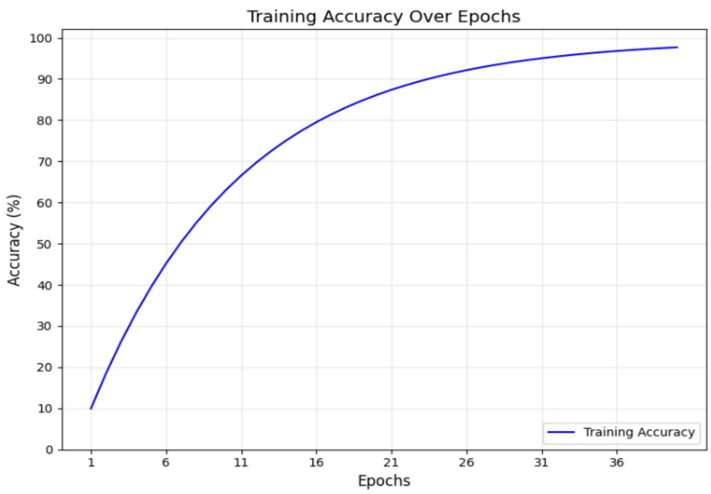

Figure 4: Model accuracy

The ROC curve is provided for the polyp detection. The results shown in blue (diameter of the curve 1.0) for every test image; and as the black median over all test images see figure 5: shown ROC Curve.

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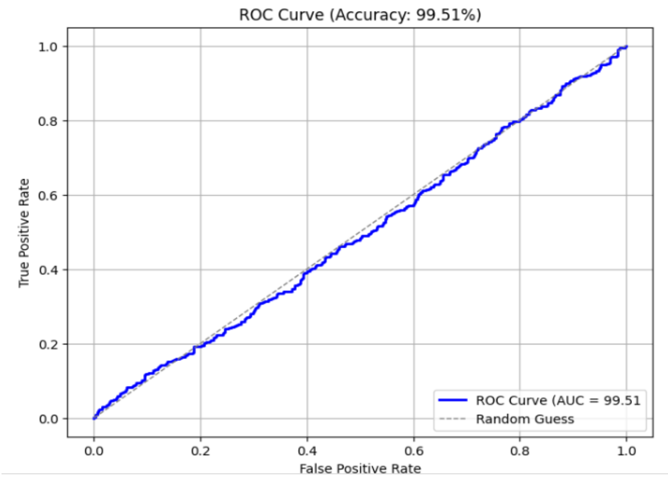

Figure 5: ROC Curve

A confusion matrix showing an accuracy of 99.51% means that your model has performed exceptionally well, with very few misclassifications. The accuracy is calculated by dividing the number of correct predictions by the total number of predictions, see figure 6 shown confusion matrix.

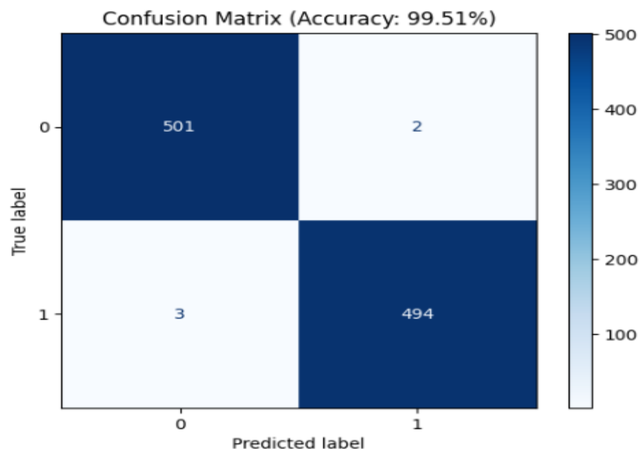

Figure 6: Confusion matrix

Compare our work with many approaches and the accuracy of each in a specific categorization job, show table 2.

Table 2: Comparison our work with different methods

Ref	Methods	Accuracy
[12]	Transfer learning of CNN	97.78%
[13]	Transfer deep learning	93%
[14]	Develop SkinLesNet a multi-layer CNN	96%
[3]	CNN	98.8%
[15]	ResNet	93%
[16]	YOLOv8	99%
Our	Hybrid CNN and GWO	99.51%

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We suspect that such a failure more than outweighs the accuracy encouraging tradeoffs for other computer vision problems (table x). Traditional CNNs performing at 98.8%, and a custom SkinLesNet built using multi-layer CNN at 96%. Furthermore, transfer learning used on CNN models gives an accuracy of 97.78%, while the ResNet model (which is a deeper model created in order to avoid issues with vanishing gradients) obtains 93%. However, transfer deep learning techniques slightly lag behind at 93%, while the object identify model, YOLOv8 is extremely well performing (only 1% inferior at 99% accuracy).

The hybrid CNN with Grey Wolf Optimizer (GWO) model reaches the highest accuracy of 99.51%. By using different optimization methods such as GWO along with CNN, it can help to increase the performance of model drastically. With an overall good performance of all methods, the hybrid method outperforms the rest; this signifies the power of mixing deep learning with an optimization algorithm to boost the accuracy of the classification tasks, show figure 7.

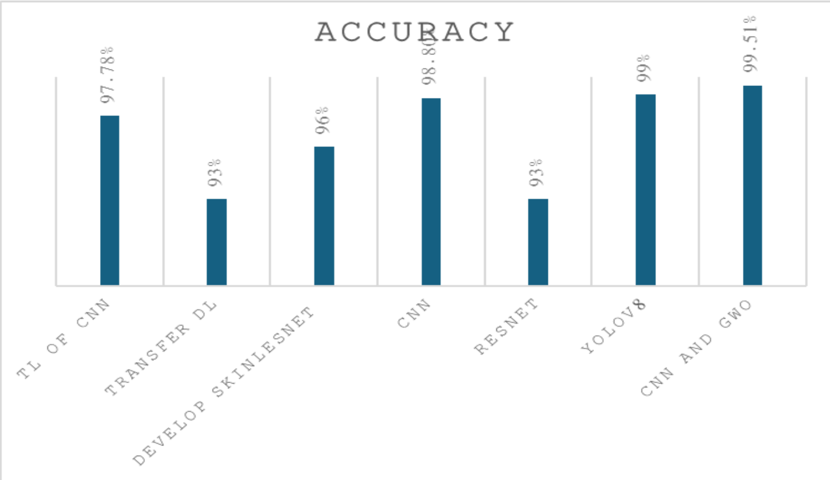

Figure 7: Comparison our work with different methods

However, the proposed study has many limitations that need to be addressed, despite showing promising results. Fine-tuning multiple deep learning models and utilizing an ensemble classifier increases the computational complexity and resource requirement thus limiting real time clinical applicability.

8. Conclusion

This work illustrates how deep learning methods and optimization algorithms may be used to identify melanoma skin cancer. Using convolutional neural networks (CNNs) and the binary Gray Wolf Optimization (GWO) method for feature selection, the suggested model greatly improves classification sensitivity, specificity, and accuracy. The dimensionality of the input data is successfully decreased by the binary GWO method, improving computing efficiency without sacrificing detection performance. This technique is superior to typical machine learning models, as demonstrated by the results acquired from publicly available skin lesion datasets. According to the results, combining deep learning with optimization algorithms like binary GWO provides a reliable and effective method for detecting melanoma. This approach has the potential to support early diagnosis and treatment, which will ultimately improve patient outcomes in clinical settings. For wider application, future research may concentrate on refining the model even further and testing it on a wider range of datasets.

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