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RESEARCH ARTICLE

An Automatic Dermatology Detection System Based on Deep Learning and Computer Vision

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ABSTRACT Automatic medical diagnosis has gained significant attention among researchers, particularly in disease diagnosis. Differentiating between dermatology diseases is pivotal in clinical decision-making as it provides prognostic and predictive information and treatment strategies. This paper proposes a dermatology detection system based on deep learning (DL) and object recognition. The proposed model consists of three phases: Data preprocessing, data augmentation, and classification with localization. In the data preprocessing phase, we apply various operations such as color transformation, resizing, normalization, and labeling to prepare the input image for enrollment in our DL models. The data augmentation phase is carried out on the input images using the convolutional generative adversarial network algorithm. In the third phase, YOLO-V5 is used to classify and localize objects. The dataset is carefully collected with the assistance of medical specialists to ensure its accuracy. The proposed models are evaluated and compared using various metrics. Our empirical results demonstrate that the proposed model outperforms state-of-the-art models in terms of accuracy. Our proposed methodology offers significant improvements in detecting vitiligo and melanoma compared to recent techniques.

INDEX TERMS Computer vision, deep learning, medical diagnosis, YOLO-V5.

I. INTRODUCTION

ARTIFICIAL intelligence (AI) and machine learning (ML) techniques have strongly promoted their application in a wide range of fields including, but not limited to, diagnostics, medical treatment, and preventive health care [1], [2], [3]. Significant advances in using AI for predicting malignancy and classifying images in dermatology [4], [5] have been made. However, using AI in clinical dermatology presents difficulties due to the inconsistency of data models, data features, and outcome metrics. In medical fields, image data is produced at an increasing rate, making it more challenging to sort and manage; AI has been created to process large amounts of data and provide useful insights, predictions, and decisions based on evidence. Computer vision is a branch of AI that allows machines to understand visual images, improving the accuracy and efficiency of analyzing medical images. [6]. Deep Learning (DL) is another powerful branch of ML that has been utilized in solving a diverse range of complex problems, such as pattern recognition, image and processing [7], [8], [9], [10], [11], [12], [13], [14], [15], [16]. Medical applications can achieve higher accuracy by utilizing DL. This is a widely accepted concept in academic and medical communities. Disease prevention, diagnosis, and prognosis rely heavily on medical imagery. Academic and medical circles have long struggled with its analysis. Inspecting images based on dermatologist experience is the traditional method

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of medical image analysis. Because dermatologists have varying experience levels, there are also discrepancies among observers.

AI decision and computer-aided diagnosis systems such as disease diagnosis [17] and thoracic illness diagnosis [18], [19] and skin lesion detection [20]. Skin diseases have a noticeable impact on a patient's psychological health, resulting in a loss of confidence and other issues. Skin diseases have a significant impact on the patient's psychological health. It can lead to a loss of confidence and even depression in the patient. Dermatologists must have adequate knowledge of AI concepts because dermatological conditions, with their abundant clinical and dermatoscopic images and data, have the potential to be the next big thing in the application of AI in medical fields. Skin diseases are among the most common diseases that affect people all over the world. Dermatological diseases refer to conditions such as melanoma, basal cell carcinoma, squamous cell carcinoma, and intraepithelial carcinoma. ML is a powerful tool that can address real-world issues by analyzing data. It has been a widely discussed topic within the field of AI for some time [7], [21]. As a result, skin diseases can be fatal. There are a variety of skin diseases that may develop in the human body as a result of causes such as excessive sun exposure, water loss, sebum production, or hereditary inheritance. There is a condition called pigmented skin disease that is quite prevalent. Melanocytes and melanin are abnormally produced, resulting in the illness.

Some pigmented skin diseases, such as freckles and perioral streaks, can be extremely bothersome to people's daily lives, even if they are not life-threatening. Visual judgment based on expertise and pathological diagnosis is the primary approach to diagnosing skin diseases in the clinic [22], [23], [24]. Skin condition diagnosis is challenging. Skin disease can be identified visually using a variety of cues, including body size distribution, color, scaling, and lesion pattern. When the individual components are analyzed separately, the identification process can become complex [25]. As a result, it is crucial to detect skin diseases early and prevent them from spreading. DL showcases its powerful knowledge discovery capabilities to boost diagnostic performance and clinical workflow effectiveness in organ and structure segmentation applications and image quality enhancement. Therefore, a thorough analysis of DL applications in medical pictures is valuable and will develop knowledge-based systems in the medical industry. Multiple medical image analysis applications rely on image registration. With the advent of DL, algorithmic performance for many computer vision applications, including mature registration, has improved significantly in recent years. Medical image remedial penetration methods using DL have exploded in popularity over the past several years. Therefore, an in-depth study of the latest algorithms in this sector is pertinent and required Wang [26]. Detecting skin diseases and various growth stages in complex and changing surroundings cannot be done using conventional approaches. The accuracy and real-time performance of DL approaches are likewise subject to trade-offs. To address these issues, the state-of-the-art used the ''You Only Look Once algorithm'' (YOLO-V5) for real-time prediction of skin diseases. The cutting-edge technology utilized the YOLO-V5 algorithm to predict skin diseases in real-time. The YOLO algorithm was first introduced in 2015 and offered a new approach to object detection by treating it as a regression problem that could be solved using a single neural network. This has resulted in significant advancements in the field of object detection in recent years, incorporating many of the most groundbreaking ideas from computer vision research. The contributions of this paper can be illustrated in the following points.

- Prepare a dermatoscopic dataset that is carefully collected and revised by medical specialists.
- Increase the amount of the image using the Convolutional Generative Adversarial Network (CGAN) data
  augmentation technique.
- Deploy DL-based object recognition models to detect the disease and split background.
- Evaluate the proposed models using evaluation metrics.
- Contrast the proposed models with the current state-of-art.

The structure of this paper comprises several sections. Related work is presented in Section II, while Section III outlines the proposed solution's components. The model's results are discussed in further detail in Section IV, and finally, Section V includes the conclusion and future work.

II. RELATED WORK

Dermatological disease detection is critical in disease prevention and diagnosis. An effective automatic skin disease detection system requires a reliable feature extraction mechanism. This process is critical when using diagnostic systems to detect diseases. Several methods for extracting and analyzing various features from skin lesion images have been proposed in the last decade. However, some things could be more consistent among observers due to readers' varying experience levels. Several researchers attempted to recognize skin diseases automatically to address this issue, and several methods for identifying and classifying skin diseases were developed and tested. The following subsections discuss the researcher's achievements in advancing the state of the art using ML and DL methods.

A. DERMATOLOGY DETECTION AND MACHINE LEARNING TECHNIQUES

Over the past few years, ML algorithms have become increasingly popular as a computational tool for clinical diagnosis, particularly in classifying pigmented skin lesions. Dalila et al. [27] provided an automated system that used four types of features to describe malignant lesions: texture, relative colors, geometrical, and qualities, which pertinent ones are chosen, along with an Ant colony-based

segmentation method. They utilized artificial neural network (ANN) and *K*-Nearest Neighbor as malignant lesions classifier. They tested the proposed segmentation algorithm by extracting and comparing the most relevant features that describe melanomas. Their automated system examined 172 dermoscopic images, 88 malignant melanomas, and 84 benign lesions. The final results demonstrated that a better classification was received and outperformed the manual one. For *K*-Nearest Neighbor classifier, the recorded accuracy was 85.22% of tested images against 87.50% for manual masks, while the Neural Network classifier correctly classified 93.60% of tested images against manual masks with an accuracy of 86.60%.

Adjed et al. [28] proposed a feature extraction technique composed of two phases. The first was based on wavelet and curve-let transforms for extracting structural features, and the other phase depended on local binary patterns for extracting textural features. Support Vector Machine (SVM) was utilized to categorize collected features. Using a dermoscopy database of 200 images, 160 were non-melanoma, and 40 were melanoma. The accuracy rate of the validated results was 86.07%, with a specificity of 93.25% and a sensitivity of 78.93%. Tajeddin et al. [29] proposed a melanoma lesions classification approach from dermoscopic images. They used contour propagation to start lesion segmentation. Lesions were mapped via log-polar space using Daugman's transformation based on the surrounding area to extract features. They used two approaches to test the effectiveness of the new characteristics: linear SVM and RUSBoost classifier to discriminate between melanoma and nevus. The proposed approach is applied to 120 images with a 10-fold cross-validation framework by using only four characteristics with the linear SVM classifier; final results of accuracy, sensitivity, and specificity of 99.2%,97.5%, and 100% respectively were recorded while the second classification system, which included eight optimum selected features in addition to the RUSBoost classifier, was tested on 200 dermoscopic images, with sensitivity, specificity, and accuracy of 95%.

Ahammed et al. [30] introduce a skin disease diagnosis model that automatically segments affected lesions. They apply three ML classifiers: Decision Tree, SVM, and *K*-Nearest Neighbor (*k*-NN). Two datasets, namely ISIC2019 and HAM10000, were used to evaluate the proposed model. The accuracy achieved for the ISIC2019 dataset was 94%, 95%, and 93% with KNN, SVM, and DT classifiers, respectively. On the other hand, for the HAM10000 dataset, the accuracy achieved was 95%, 97%, and 95% using KNN, SVM, and DT classifiers, respectively.

NPriyadharshini et al. [31] proposed a classification model that utilized Principal Component Analysis (PCA) for feature selection, Fuzzy C-Means (FCM) for skin image segmentation, and ELM-TLBO: Extreme Learning Machine (ELM) and Teaching-Learning-Based Optimization (TLBO) for classification. The model achieved a classification accuracy of 93.18% in detecting melanoma skin cancer, which is significantly better than the accuracy achieved by SVM, Convolutional Neural Network (CNN), and Logistic Regression, which are 78.11%, 83.25%, and 78.21%, respectively.

B. DERMATOLOGY DETECTION AND DEEP LEARNING

DL models outperform ML models as they automatically define and select problem features, and more accuracy is attained if it is trained with more data. Gonzalez-Diaz et. al. [32] introduced CNN-based skin lesion CAD system called DermaKNet. The authors added a modulation block to the outputs of the convolutional res5c layer before building the proposed CNN on top of ResNet50. AVG and Polar AVG, two pooling layers, were developed simultaneously. The final stage of CNN used three entirely connected layers. The asymmetry block comes before the third fully connected block because of the numerous ways melanoma grows. Using the asymmetry block, various melanoma development mechanisms were discovered. Amin et al. [33] introduced a model composed of three phases. In the first phase, images were resized, and only the luminance (L) channel was selected. The Biorthogonal 2-D wavelet was transformed in the second phase, and the Otsu algorithm was utilized for skin lesion segmentation. Finally, PCA, pre-trained Alex net and VGG16 were utilized for deep feature extraction. Pezhman et al. [34] proposed a model from scratch based on CNNs for skin lesions and dermoscopic feature segmentation. They introduced increasing input depth to convolutional layers using CIELAB color space and RGB color channels of the original dataset image instead of using traditional augmentation or transfer learning of pre-trained models. The proposed model applied to two datasets provided by The International Skin Imaging Collaboration (ISIC), ISIC 2016 and ISIC 2017. The Jaccard index shows a 2% increase, and accuracy improved by 7% in comparison to the results of the ISIC 2017. The model also showed a 1% increase in the Jaccard index and a 6% improvement in sensitivity for the ISIC 2016 challenge. Kassem et al. [35] utilized GoogleNet and pre-trained models to develop a DL algorithm that can accurately categorize various types of skin lesions from the ISIC 2019 dataset. The model successfully classified eight different classes of skin lesions with high percentages of classification accuracy, sensitivity, specificity, and precision, which were measured at 94.92%, 79.8%, 97%, and 80.36%, respectively. Srinivasu [36] proposed a model for classifying skin illnesses, which was based on MobileNet V2 and Long Short-Term Memory (LSTM). A grey-level co-occurrence matrix was utilized to evaluate the progression of pathological growth. The effectiveness of the proposed model was then tested using the HAM10000 dataset, and the final outcome showed an accuracy rate of 85%. In a recent study by Zhou et al. [37], a DL model was proposed for skin disease classification. The model combines preprocessing, data augmentation, and residual networks. Dermatologists manually annotated images, after

which background information was masked with unique colors. Sample-balanced training and testing data were generated for augmentation. Finally, the DL networks were trained to compare the performance of classifiers for different background information. The model was evaluated using a dataset with seven types of skin diseases from the Department of Dermatology, Xiangya Hospital. The results showed that the classifier trained on the green background outperformed the other backgrounds, with a precision of 81.98% and an F1-score of 82.41%.

III. PROPOSED APPROACH

The proposed model consists of three phases: Data preprocessing, data augmentation, and classification with localization. In the data preprocessing phase, we apply various operations such as color transformation, resizing, normalization, and labeling to prepare the input image for enrollment in our DL model. It also includes dataset splitting into train, validation, and test subsets. Regarding the validation, we deployed the k-fold technique with k of 10. The data augmentation phase is carried out on the input images using the convolutional generative adversarial network algorithm. In the third phase, YOLO-V5 is used to classify and localize objects. The proposed DL model is based on cascaded YOLO models which deploys three YOLO-V5 models to obtain the optimal performance. The main idea is to obtain the best weights from a YOLO model and feed it into the next one. This approach ensures efficient performance for both classification and localization. Figure 1 depicts the proposed model.

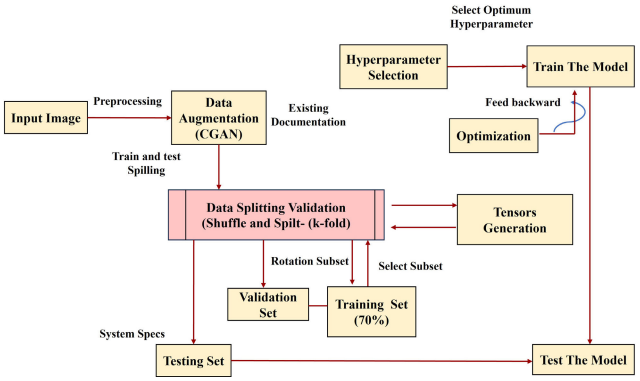


FIGURE 1. The Proposed dermatology detection DL model.

A. CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORK DATA AUGMENTATION

This study proposes a data augmentation method based on a generative adversarial network, which has been used to recognize skin from skin-captured images, as shown in Figure 2. This algorithm consists of two stages. The first is the generator stage, in which the generator network generates samples. Moreover, the second is the discriminator stage to construct the generated images. The deployed CGAN algorithm generates multiple input images to make them compatible with the nature of DL models. However, CGAN data augmentation is used to identify dermatological cases from the obtained images. The input images are transformed into feature maps by the generator network, and the discriminator uses a classification layer to distinguish between genuine and produced images based on these maps. On the other hand, when compared to other studies., our approach limits the application of GANs to the data augmentation stage, eliminating the need for classification since the objective is to produce images rather than make a decision. CGAN is used in this paper. The generator consists of five convolutional transposition layers (Conv2D Transpose). Each Conv1, Conv2, Conv3, Conv4, and Conv5 layer has 8, 4, 2, 1, and 1. The input images are initially fed into a de-noising layer that is fully connected, with a size of 8864. Then, they undergo a sequence of Conv2D Transpose layers and batch normalization layers (BN) to generate a feature map of the input images.

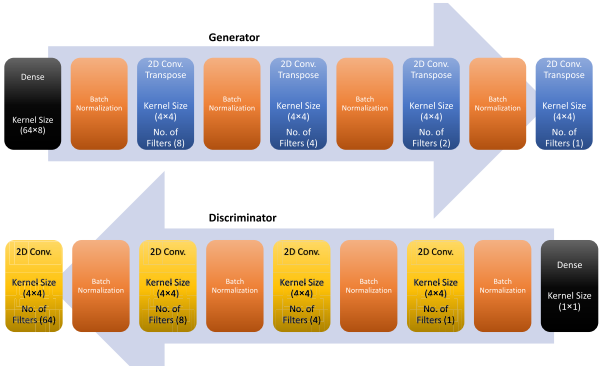


FIGURE 2. Proposed data augmentation method.

B. YOLO-5 ALGORITHM

In 2016, Joseph Redmon and his coworkers introduced the You Only Look Once (YOLO) approach [38], which used a single neural network to perform all of the necessary processes for recognizing an object. It changes the definition of object detection from picture pixels to box coordinates and class probabilities, which is a single regression problem. This integrated model simultaneously predicts multiple bounding boxes and class probabilities for objects covered by boxes. YOLO algorithm showed speed and accuracy in detecting and calculating object coordinates compared to the top methods at its release. As previously stated, an advanced YOLO-V5 detector is utilized in the proposed solution to resolve the problem in an automated manner. YOLO-V5 is created by combining Yolo-1 and Yolov-4. It excelled in the Pascal VOC (visual object classes) and Microsoft COCO official object detection datasets (common objects in context). As shown in figure 3, Yolo-5's network architecture consists of three essential elements: the backbone, the neck, and the head [39]. The first part of the process is called the Backbone, which is responsible for collecting important image features. YOLO-V5 has integrated cross-stage partial networks into Darknet, resulting in a new backbone called CSPDarknet. Compared to YOLO-v3's Darknet53, CSPDarknet is much

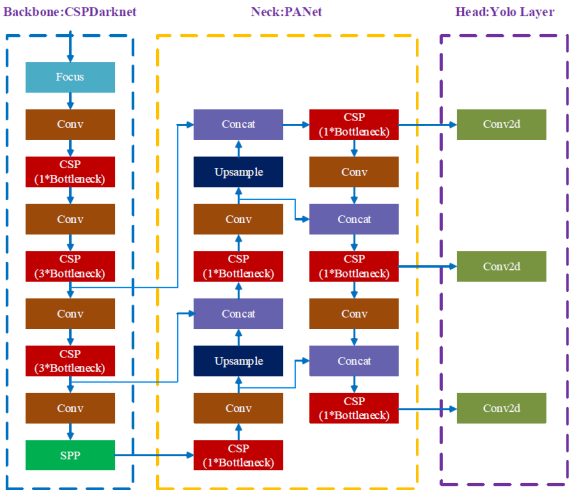


FIGURE 3. The architecture of YOLO-5 [39].

faster at processing while still maintaining or even improving detection accuracy [40]. The second component, the Neck, is primarily used to produce feature pyramids, which enable YOLO-V5 to generalize the object scaling to identify the same item in various sizes and scales. Path Aggregation Network (PANet) is employed in YOLO-V5 Neck as a parametric polymerization technique for different bone and detector levels. The adaptive feature pools of PANet connect the feature grid to every feature layer. Consequently, critical information extracted from each feature layer can be transferred straight to the planned subnetwork [26]. In both YOLO-v3 and v4, the final detection stage is carried out by the Head portion. This part creates anchor boxes for feature maps and generates output vectors that include class probabilities and bounding boxes for identified objects [39].

In our investigation, we selected Yolov5 for three reasons.

- First, YOLO-v5 integrated a cross-stage partial network (CSPNet) called CSPDarknet and created the backbone of Darknet. This was done to improve the speed and accuracy of inference and reduce model size. CSPNet addresses the problem of recurring gradient information in large-scale backbones by embedding gradient changes into the feature map. The resulting reduction in model parameters and FLOPS improves the efficiency of inference on edge devices with limited resources. Given the importance of fast and accurate detection of forest fires, the compact model size is especially valuable in enabling efficient inference on these devices.
- Second, YOLO-V5 employed a path aggregation network (PANet) as its neck to enhance information flow. Low-level feature propagation is enhanced by PANet's usage of a new feature pyramid network (FPN) structure with an enhanced bottom-up path. Adaptive feature pooling, which connects the feature grid and all feature levels, is also utilized to propagate important information directly from one feature level to the next subnetwork. The object's location accuracy increases as PANet improves the use of precise localization signals in lower layers. A change in the course of fire evolution.
- Third, to perform multi-scale prediction, the YOLO layer, the head of YOLO-V5, generates feature maps in three distinct sizes (18, 18, 36, 36, and 72 72), enabling the model to handle tiny, medium, and large objects. Typically, a forest fire develops from a small (ground fire) to a medium (trunk fire) to a significant (fire) fire (canopy fire). The model can track size changes as the fire develops, thanks to multi-scale detection.

There is a compound loss in the YOLO family that is calculated based on:

- Objectness score, an evaluation of how well the detector recognizes the objects.
- Probability score for the class, an evaluation of how well the detector identifies object classes.
- Predict localization boxes using the bounding box regression score in object detection approaches. Ultralytics used PyTorch's Binary Cross-Entropy with Logits Loss function to calculate class probability and object score. In YOLO-v5, the Leaky ReLU activation function is used in the middle/hidden layers, and the sigmoid activation function is used in the final detection layer.

The proposed DL model is based on cascaded YOLO models which deploys three YOLO-V5 models to obtain the optimal performance. The main idea is to obtain the best weights from a YOLO model and feed it into the next one. This approach ensures efficient performance for both classification and localization

TABLE 1. Dataset description.

Model	Training	Testing	Validation	Total
Melanoma	1508	325	325	2158
Vitiligo	287	62	62	411
Total	1795	387	387	2569

TABLE 2. Parameters evaluating for the suggested models.

Model	Parameters
YOLO-V5	Epochs: 100 Batch Size = 16 Total Number of Parameters = 7257791 Trainable Parameters = 7257791 Non-trainable Parameters = 0 Loss function = binary_Crossentropy

IV. EXPERIMENTAL RESULTS AND COMPARISONS

This section presents the results of our proposed models and an evaluation of the datasets used for training and testing. The final results were obtained by averaging all the evaluation metrics To assess the performance of our models, we have included the datasets used in Subsection IV-A. We have also provided workplace characteristics in Subsection IV-B and performance indicators in Subsection IV-C. Finally, Subsection IV-D presents a comparative analysis.

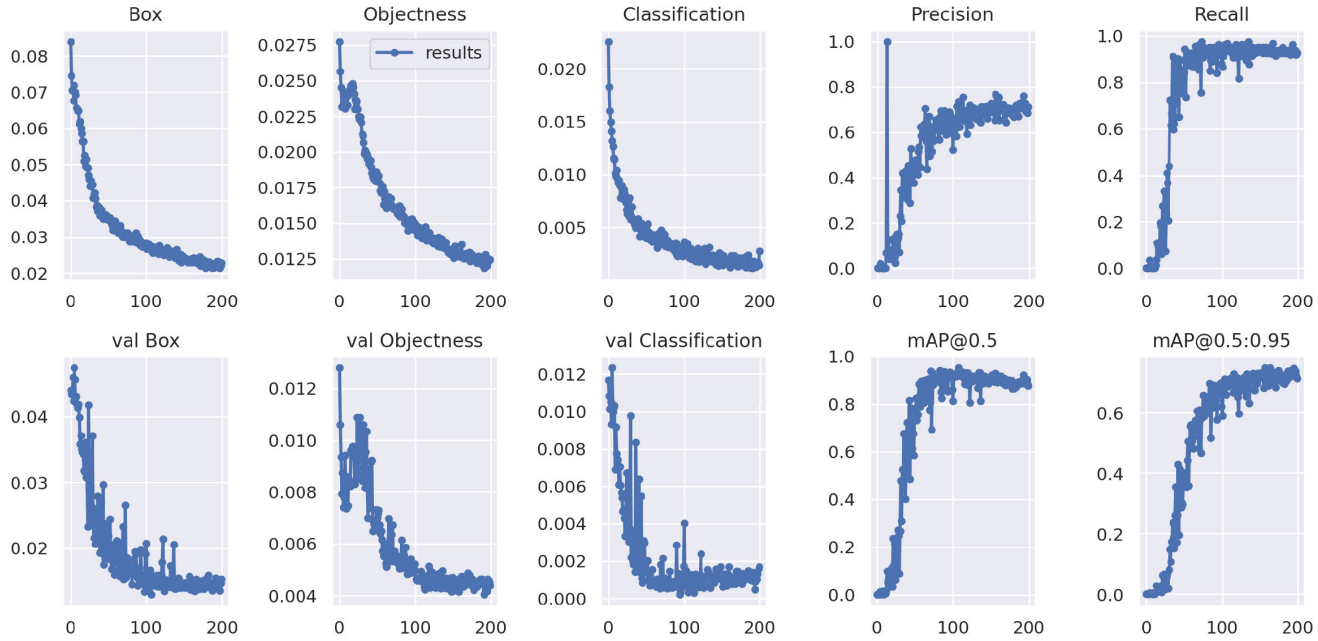


FIGURE 4. YOLO-V5 model1 results.

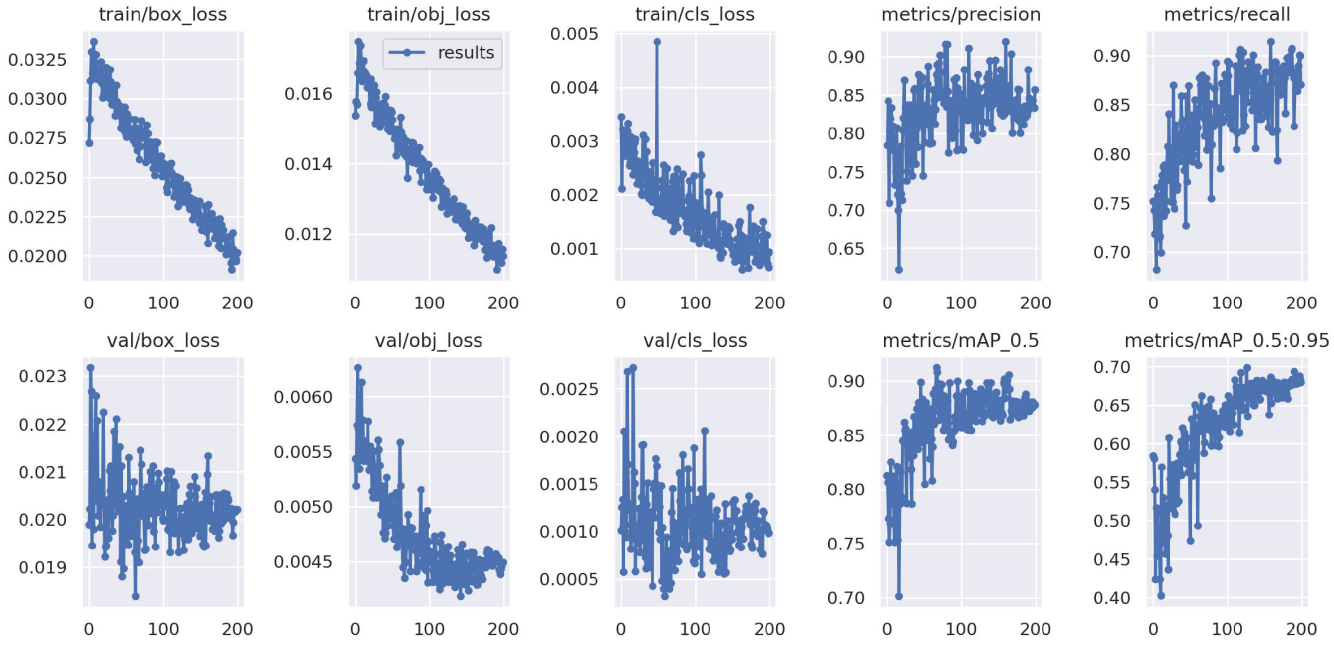


FIGURE 5. YOLO-V5 model2 results.

A. DESCRIPTIONS OF DATASETS

The datasets applied in the current research are called Melanoma and Vitiligo [41]. The melanoma dataset contains all the PLCO research data accessible for melanoma cancer incidence and death analyses. Vitiligo dataset is a skin disease that causes blotches of skin color to fade. The datasets (melanoma and vitiligo) used and their characteristics are the focus of this work. To structure the model, 70% of each dataset was selected as training data. The validation and testing data consisted of 15% each. The classification process was run across 200 epochs, and the final results were obtained by averaging all the outcomes.

Table1 shows dataset description. In the Validation stage, there are a total of 387 images, with 325 belonging to the Melanoma dataset and 62 to the Vitiligo dataset. The training stage encompasses 1797 images, comprising 1,508 melanoma images and 287 Vitiligo images. In the Test stage, there are 387 images, with 325 categorized as Melanoma and 62 as Vitiligo. Consequently, the grand total across all stages amounts to 2569 images. Specifically, there are 2158 Melanoma images distributed across the stages

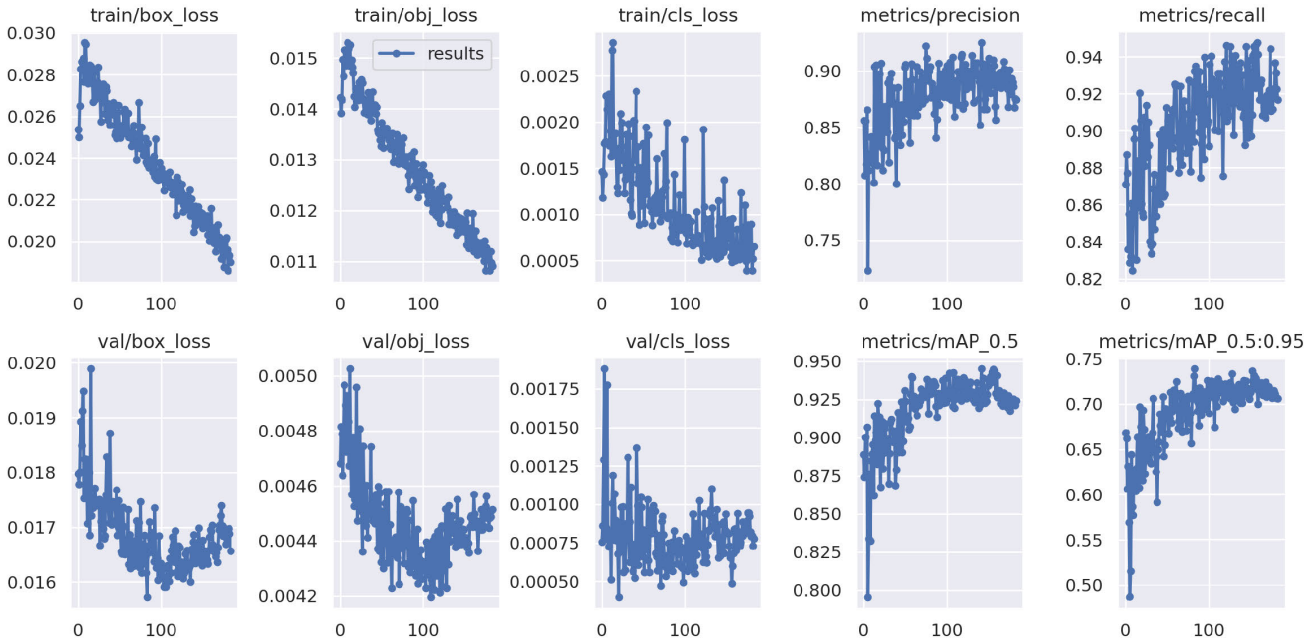


FIGURE 6. YOLO-V5 model3 results.

(325 in Valid, 1508 in Train, and 325 in Test) and 411 Vitiligo images (62 in Valid, 287 in Train, and 62 in Test). Here is the link to access our dataset:[1]

B. WORKING ENVIRONMENT

The simulation has generated its results through the utilization of powerful hardware, specifically an Intel Core i7 CPU, 64 GB of RAM, and an NVIDIA GTX 1050i GPU. Additionally, Python and PyTourch were utilized as programming tools to carry out the necessary programming tasks. Table 2 presents the recommended hyperparameters for the proposed models, while other standard parameter options, including the loss function and maximum number of epochs, are also available. The chosen optimizer for this task is Adam, and the loss function that was applied is shown in Table 2.

C. EVALUATION MEASURES

In order to increase the statistical significance of the experimental results, the proposed model's performance is evaluated using the standard metrics listed below:

1) **Accuracy**: a ratio shows how many samples are predicted successful, or true positive (*TP*), to the total number of samples and is computed using Eq.(1).
2) **Precision**: a ratio indicates how many samples are predicted to be *TP* are actually positive and evaluated using Eq.(2) where *FP*, stands for false positive, is the number of samples which are predicted as positive and are actually negative.
3) **Recall**: measures the correctly predicted positive samples out of all actual positive samples as formulated in Eq.(3), where *FN* refers to the number of samples that are predicted to be negative and are actually negative.

Additionally, **ROC-AUC**, stands for "Area Under the Curve" of the Receiver Operating Characteristic," is used to represent the model's performance graphically as the plot of Recall against Precision at different settings [42].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

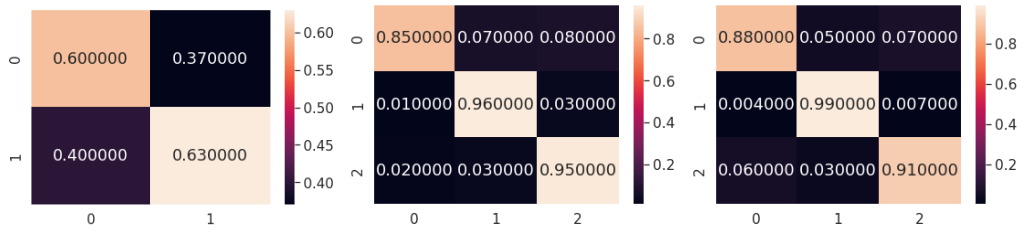
$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

D. RESULT DISCUSSION

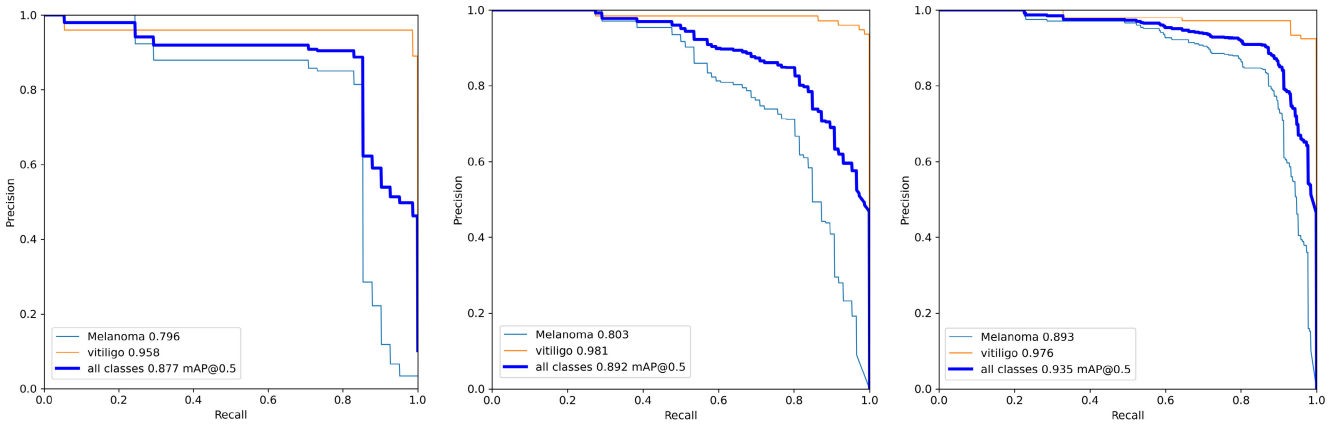
This paper proposes a DL method for skin disease detection. This study identifies two types of skin diseases (melanoma and vitiligo). This study proposes different models of the YOLO-V5 technique. The objective of the proposed method is to distinguish the infected area from the background skin. The proposed methods have been trained, validated, and tested using evaluation metrics. Figures 4, 5 and 6 show the training curves for the proposed techniques, which include the values of box, objectiveness, classification, precision, and recall during the training phase. It can be observed that the performance increases along the training process. Furthermore, the proposed techniques are tested and evaluated using the evaluation metrics. Figure 7 shows the proposed techniques' confusion matrix, which comprises the normalized value of the detected skin diseases. It can be observed that they achieved an accuracy of detection of 90 % and 97 % for melanoma and vitiligo skin diseases, respectively. Moreover, the figure shows examples of the resulting real-state images with a detection contour to

[1] https://github.com/Mohamed-Elredeny/An-Automatic-Dermatology-Detection-System-Based-on-Deep-Learning-and-Computer-Vision.git



(a) YOLO-V5 Model1 (b) YOLO-V5 Model2 (c) YOLO-V5 Model3

FIGURE 7. The confusion matrix of the proposed models.



(a) YOLO-V5 Model1 (b) YOLO-V5 Model2 (c) YOLO-V5 Model3

FIGURE 8. ROC curve of the proposed models.

TABLE 3. Comparison with the status of arts.

Item	Reference	Dataset	Algorithm	Performance
Melanoma	Khan et al., [43]	ISIC Melanoma dataset2020	ResNet-101	ACC =80%
	Liu et al., [44]	ISIC Melanoma dataset2020	Enhanced Fish Migration Optimizer (EFMO) .	ACC =80%
	Pereira et al., [45]	SKINL2 dataset	Multiple Instance Learning (MIL) and DL	ACC =80%
	Kaur et al., [46]	ISIC Melanoma dataset2020	LCNet model	ACC= 90.48%
	Proposed Model	ISIC dataset 2020	YOLO v5	ACC=91%
Vitiligo	Khan et al., [47]	Vitiligo disorder	stack ensemble of deep and conventional image segmentation (SEDCIS)	ACC=97%
	Guo et al., [48]	DSLR dataset	YOLO v5	ACC=92.91%
	Saini & Singh [49]	Vitiligo dataset	KNN, GLCM, K-means, and voting classifier	ACC=75%
	Proposed Model	Vitiligo Dataset	YOLO v5	ACC=99%

visualize the ability to perform the proposed methods on real-life applications. When IOU is between 0.5 (or 50%) and 0.95 (95%), we used many measures to assess the model's performance, including Precision, Recall, and mAP (mean average Precision). The graphs of the metrics curves as training advances are shown in Figure 8. Using a variety of metrics, including Precision, Recall, and mAP (mean average Precision) when IOU is between 0.5 (50%) and 0.95 (95%). The proposed YOLO-V5 model1 had a validation precision score of 0.887, a recall score of 0.927, and mAP scores of 0.877 for melanoma and vitiligo, respectively. The results demonstrate the accuracy of our method in correctly predicting the signs performed in various environments. In addition, the proposed YOLO-V5 model2 had a validation precision score of 0. 916, a recall score of 0.887, and mAP scores of 0.892 for melanoma and vitiligo, respectively. With these results, it is clear that our approach is highly effective in accurately predicting signs performed in various environments. Notably, our YOLO-V5 model3 achieved a validation precision score of 0.877, a recall score of 0.99, and mAP scores of 0.935 for melanoma and vitiligo, respectively. These impressive scores demonstrate the reliability and accuracy of our approach, further supporting its potential value in real-world applications. To ensure accurate performance in different scenarios, it's important to evaluate certain parameters. One such parameter is accuracy, which measures how often a model predicts the correct outcome. This can be calculated by dividing the classifier's correct predictions by the total number of predictions. The precision-recall curve demonstrates how precision and recall are related at various threshold values. A greater area beneath the curve suggests high precision and recall, where high precision implies a low false positive rate and high recall.

E. COMPARISON WITH THE STATE-OF-THE-ART MODELS

Table3 compares the proposed models with the recent models using various datasets that detect melanoma and Vitiligo. The proposed YOLO-V5 model ranked first in all performance accuracy. It is important to note that the choice of YOLO-V5 depends on various factors, including DL and integrated cross-stage partial network. CSPDarknet created the backbone of Darknet, improving the proposed image's speed and accuracy.

V. CONCLUSION AND FUTURE WORK

Distinguishing between dermatology diseases is key in clinical decision-making as it provides prognostic and predictive information and treatment strategies. This paper proposes a dermatology detection system based on DL and object recognition. The suggested approach contains three stages: Data preprocessing, data augmentation, and classification with localization. In the first stage, different procedures, such as color transformation, resizing, normalization, and labeling, were applied to prepare the input image for enrollment in our DL models. The data augmentation stage is implemented on the input images using the convolutional generative adversarial network algorithm. In the third stage, YOLO-V5 is used to classify and localize objects. The dataset was carefully collected with the assistance of medical specialists to ensure its accuracy. The proposed models were assessed and compared using various metrics. Our empirical results demonstrated that the suggested model surpasses state-of-the-art methods in accuracy. Our suggested method offered considerable advancements in detecting vitiligo and melanoma compared to recent approaches. Overall, the proposed model makes substantial progress in the early detection of dermatology diseases through image data analysis, potentially impacting the medical field positively. With further refinement, validation, and interpretability enhancements, they could become valuable tools in supporting healthcare professionals in dermatology disease classification and advancing medical research.

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