Early Detection Of Skin Cancer With Classifications Using Deep Learning

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Abstract— **Detecting skin cancer in its early stages is crucial for better prognosis and preventing metastasis. Automating the preliminary screening process can optimize healthcare resources, allowing clinicians to focus on confirming diagnoses and prescribing appropriate treatment plans. In this research, a skin cancer detection system incorporating an advanced deep learning algorithm called YOLOv8 is presented. The study focuses on identifying various types of skin cancer and involves preparing a labelled dataset of skin cancer images, annotating bounding boxes around lesions, configuring YOLOv8, and training the model. The proposed system has significant potential for medical imaging applications, providing an efficient and early diagnostic tool for skin cancer. The integration of YOLOv8 can aid in improving patient outcomes and establishing a valuable resource for the medical community in the realm of skin cancer diagnosis.**

Keywords— skin cancer, Deep Learning (DL), YOLOv8, Annotating Bounding Boxes

I. INTRODUCTION

The skin is the external layer of the human body, comprising multiple layers that include immune cells and melanin-generating cells to protect against ultraviolet radiation. Skin cancer is the most prevalent type of cancer worldwide, with melanoma and non-melanoma pigmented lesions being the two primary types[1]. Melanoma is more deadly than non-melanoma since it can spread to other body areas if not detected and treated promptly, and is associated with melanocytes that cause malignant cells to change colour. The American Cancer Society predicts that about 97,610 new melanomas will be diagnosed in the country in 2023, with approximately 7,990 people predicted to die from it. Early detection is crucial to increase survival rates, as melanoma rates have considerably increased in recent decades[2]. Visual analysis is difficult due to the significant similarities between the different forms of skin lesions, which can lead to incorrect diagnoses. Researchers have developed computer-aided diagnosis (CAD) systems that integrate image processing, pattern recognition, and artificial neural networks to assist physicians in diagnosing melanoma. The goal is to increase early detection rates, which can save lives. Various machine learning algorithms and classifiers are utilized to extract features and categorize the disease. Melanoma is a serious form of skin cancer that can be deadly. Detecting it in its early stages is crucial for successful treatment and improved health outcomes, as it can be challenging for individuals to identify melanoma independently due to its resemblance to other skin lesions

A. Deep Learning

a 2% improvement

Deep learning is a form of AI that automates prediction-based analysis by comprehending the courses of several outcomes and emulating the learning process of humans[3]. To train a network for a task like object detection in images, we label a dataset of images, and the network learns to recognize unique features and associate them with categories. Successive layers pass on information to the next layer, increasing the complexity and detail of learning. The network learns directly from acquired data, and the user has no control over the details learned by the algorithm.

B.   YOLO Algorithms

YOLO is nothing but You Only Look Once is a real-time object detection algorithm which was developed by Joseph Redmon and Ali Farhadi in 2015[4]. This algorithm uses a convolutional neural network (CNN) to predict the bounding boxes and class probabilities of objects in input images.

Since its inception in 2016 until the last year (2023), the YOLO family has continued to evolve at a rapid pace. Although the initial author (Joseph Redmon) halted furtherwork within the computer vision domain at YOLO-v3, the effectiveness and potential of the core 'unified' concept havebeen further developed by several authors, with the latest addition to the YOLO family coming in the form of YOLO-

v8.

Figure 1.1. YOLO Evolution Timeline

YOLO-v1 was introduced in 2015, proposing the concept of imposing a grid cell with dimensions of s×s onto the image, where the grid cell responsible for detecting an object was determined by the centre of the object falling into one of the cells[5]. YOLO-v2/9000 introduced batch normalization to improve model convergence, resulting in
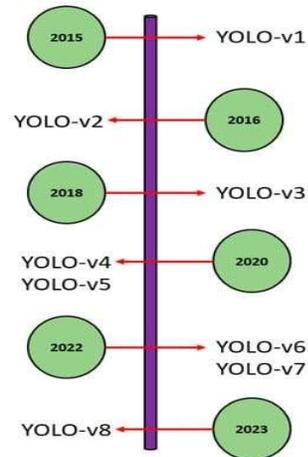
in mean average precision compared to the original YOLO. YOLO-v3 was developed in 2018, combining aspects of YOLO-v2, Darknet-53, and residual networks, allowing for the preservation of fine-grained features and multi-scale detection. YOLO-v4, released in 2020, introduced anchor boxes for object localization. YOLO-v5 also released in 2020, utilized dynamic anchor boxes for object localization[6]. YOLO-v5, also released in 2020, utilized dynamic anchor boxes and a single neural network to process the entire image. YOLOv6 is a single-stage object detection framework designed for industrial applications, with better performance than YOLOv5. YOLO-v7, released shortly after YOLO-v6, proposes architectural and trainable bag-of-freebies reforms to improve accuracy and speed.

1) YOLO-v8

Ultralytics confirmed the release of YOLO-v8 in January 2023, which is the latest addition to the YOLO family of algorithms and was released alongside YOLO-v5. Initial comparisons of YOLO-v8 with its predecessors demonstrate its superiority as the new YOLO state-of-the-art[7]. Figure 8 shows that when comparing YOLO-v8 against YOLO-v5 and YOLO-v6, all YOLO-v8 variants output better throughput with similar parameters, indicating hardware-efficient, architectural reforms. Ultralytics presented YOLO-v5 for impressive real-time performance, and YOLO-v8 is expected to focus on constrained edge cancer deployment at high-inference speed, based on the initial benchmarking results.
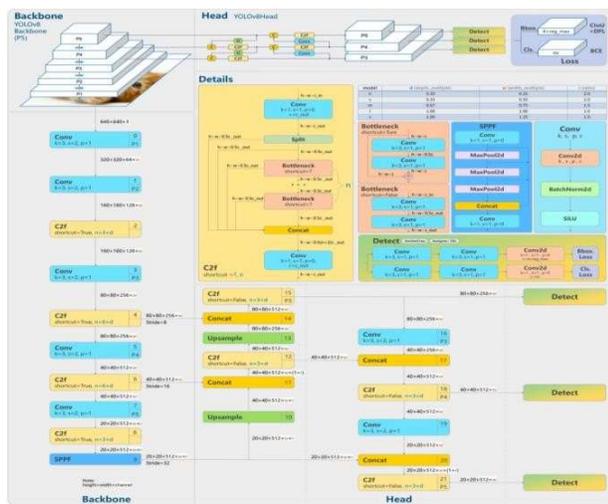

Figure 1.2 YOLO-v8 Architecture

II. LITERATURE REVIEW

A recent paper presented at the 2022 International Conference on Disruptive Technologies for Multi-Disciplinary Research and Applications (CENTCON) proposes a fully automated method for diagnosing dermatological conditions from lesion data. S. Bhargavi et al highlight the challenges of human interpretation and the importance of early diagnosis for fatal illnesses like melanoma. Automated methods can provide a more cost-effective and efficient way of diagnosing dermatological conditions, particularly when a group of images contains a variety of diagnoses. The proposed method involves data collection, preprocessing, and output prediction

using a support vector machine. Preprocessing includes removing hair and shade from the data to improve prediction accuracy[8].

Javaid. A et al proposed a method for skin lesion classification and segmentation using image processing and machine learning. The proposed method uses contrast stretching of dermoscopic images, followed by the OTSU thresholding algorithm for image segmentation. Features including Gray level Co-occurrence Matrix (GLCM) features, the histogram of oriented gradients (HOG) object, and colour identification features are extracted from the segmented images. The feature vector is then standardized and scaled, and a novel approach of feature selection based on the wrapper method is proposed before classification. The proposed system achieved a maximum classification accuracy of 93.89% using the Random Forest classifier on the publicly accessible dataset of ISIC-ISBI 2016. The proposed approach of contrast stretching before the segmentation gives satisfactory results of segmentation[9].

R. S. Kumar et al emphasize the importance of early detection in identifying melanoma and increasing the chances of a cure. They conducted a literature survey of multiple methods used for skin cancer classification before introducing their methodology, which uses a Convolutional Neural Network (CNN) to identify and diagnose skin cancer using the IS IC dataset consisting of 2637 images. Their proposed model achieved an accuracy of 88% for classifying the training dataset as either benign or malignant, highlighting the potential of AI-powered solutions for early and accurate detection of skin cancer[10].

This research paper by D. C. Malo et al evaluated the effectiveness of using CNN to detect skin cancer by classifying benign and malignant moles. They utilized the ISIC dataset containing 2460 coloured images, with 1800 used for training and 660 for testing. The authors presented a detailed workflow and used Keras and TensorFlow to structure their model. Their proposed VGG-16 model achieved an accuracy of 87.6% after modifications to parameters and classification functions. Overall, the study highlights the potential of CNN models in detecting skin cancer[11].

The experimental research setup by Y. Nie et al. discusses the challenges of detecting melanoma due to the visual similarity between benign and malignant dermoscopic images. The authors present the You Only Look Once (Yolo) algorithms that utilize DCNNs for melanoma detection. Yolo algorithms involve resetting the input image size and dividing it into cells to predict the bounding box of the object and the class confidence score. The test results show that Yolo algorithms achieve a mean average precision (mAP) of over 0.82 with a training set of only 200 images. This finding highlights the potential of Yolo algorithms for detecting melanoma in lightweight system application[12].

Manoj Prabhakaran K et al developed a research based on Yolo deep neural network which was proposed for classifying

9 types of skin cancer. The training phase involves a data augmentation process to improve classification efficiency. A bounding box is used to preserve the prominent features of the image and identify the object of interest during testing. Yolo V3 and Yolo V4 are both tested for classification. The proposed network achieves an average precision score of 88.03% and 86.52% for Yolo V3 and Yolo V4, respectively, on a dataset of 4389 images divided into nine classes. The trained network is evaluated statistically using accuracy, precision, recall, and F1 score with average scores of 98.06%, 92.75%, 91%, and 92%, respectively[13].

III. METHODOLOGY

The primary objective of this research study is to develop and evaluate an AI model that can predict skin cancer based on skin images. To achieve this objective, the researchers have established several goals. Firstly, the aim is to develop an AI model inspired by YOLO-v8 that can effectively capture spatial relationships within volumetric medical data. Secondly, plan is to evaluate the model's performance by employing standard metrics, including classification reports and confusion matrices on test data to determine its mAP value. Additionally, the aim is to create interactive tools that allow for dynamic exploration of image annotations, enabling a more comprehensive understanding of the AI's decision-making process. Finally, this research study aims to contribute to the advancement of medical image analysis and predictive modelling in skin cancer research by providing a versatile and interpretable AI model.
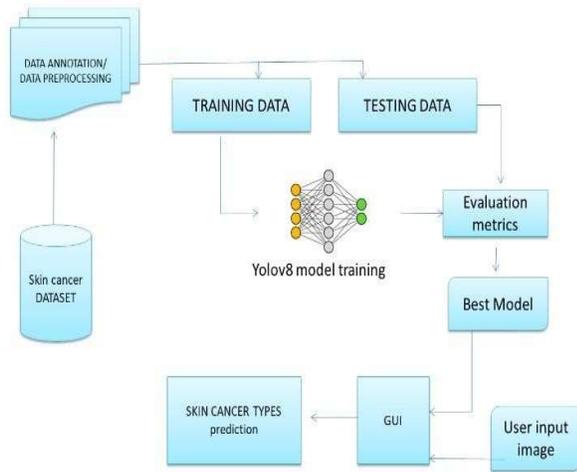

Figure 3.1 Flowchart

A. Data Collection

The data used in this project was sourced from the Kaggle, which has 9 distinct classes each assigned with a numerical label. This information is crucial for training a machine learning model to detect skin cancer. The numerical labels and class names are necessary to annotate the images correctly during the labelling process, configure the model's output layer, and interpret its predictions during evaluation.

Data Annotation

For supervised machine learning models to be successful, datasets must be accurately labelled through data annotation, which establishes the foundation for training data infrastructure. The data annotation process involves identifying patches through bounding boxes and labelling them. To prepare the images for training, they are pre-processed by rotating them 90 degrees and flipping them.
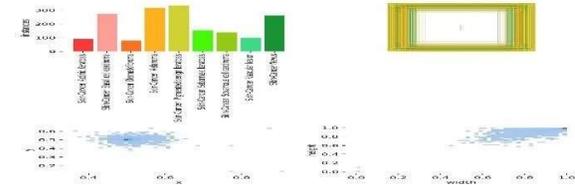

Figure 3.2 Annotation and Labelling

B. Model Training

System architecture refers to the conceptual model that outlines the structure, behaviour, and other views of a system. It involves a formal representation and description of a system, organized to support reasoning about its structures and behaviours. The model is trained using the YOLOv8 architecture which features a new backbone network, anchor-free detection head, and loss function. The YOLOv8 model infrastructure has been updated to show the new backbone and head structures, including the replacement of the C3 module with the C2f module. YOLOv8 now features anchor-free bounding boxes, eliminating the need for users to manually identify anchor boxes to facilitate object detection. Calculating the offset from the boundaries to the predicted object helps the model identify the object's location better.
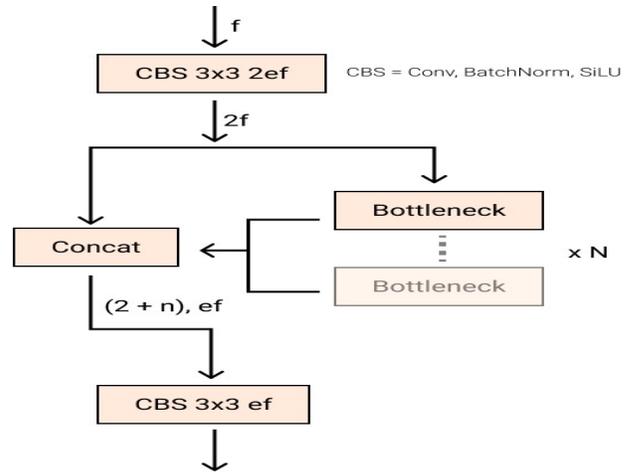

Figure 3.3 C2f Module

During training, YOLOv8 uses augmentations, including Mosaic augmentation, a process that combines four images to teach the model about new object locations, occlusion, and surrounding pixels variation. However, using Mosaic augmentation throughout the entire training process can negatively impact prediction accuracy. Therefore, YOLOv8 stops the process in the final epochs of training to optimize the training pattern.

4

Figure 3.4 Train Batches

The primary reason for YOLOv8's popularity is its big boosts to performance accuracy and efficiency during inference and training. Ultralytics, the authors of YOLOv8, have provided useful sample data that highlights the model's superiority over other versions of YOLO. The model outperforms YOLOv7, YOLOv6-2.0, and YOLOv5-7.0 in terms of mean Average Precision, size, and latency during training. The largest YOLOv5 model, YOLOv5x, achieved a maximum mAP value of 50.7, while YOLOv8 models consistently outperform YOLOv5 across all sizes. Overall, YOLOv8 represents a significant improvement from YOLOv5 and other competing frameworks.

C. Model Testing

To assess the accuracy of a YOLOv8 model, it is important to evaluate its performance on a separate testing set, which is a dataset that the model has not seen during training. Two common plots are used to evaluate the performance of the trained model: the accuracy plot and the loss plot.

The accuracy plot shows how well the model performs on the testing set as the number of training epochs increases. Accuracy is typically measured as the percentage of correctly classified samples in the testing set. As the model is trained, its accuracy on the testing set typically increases, but may eventually plateau or even decrease due to overfitting.

The loss plot shows the change in loss or error on the training and testing sets as the number of training epochs increases. The loss is usually measured as the difference between the predicted output of the model and the true output. The loss should decrease as the model is trained, indicating that the model is improving its ability to make predictions by graphical user interface (GUI)

Both plots are important for evaluating the performance of a YOLOv8 model. The accuracy plot provides a measure of how well the model generalizes to new data, while the loss plot indicates whether the model is learning from the training data. By using these plots, the user can determine whether the model is performing well and make necessary adjustments to improve its accuracy.

IV. EXPERIMENTAL RESULT AND ANALYSIS

The purpose of this section is to give you an overview of the research interface and the processes involved.

Figure 4.1 Overall Output

The first column shows the training epoch or iteration number, representing one pass through the entire training dataset. The next columns display the loss associated with bounding box predictions, classification, and dense feature learning. These losses measure how accurately the model can predict the locations of objects and classify them as either "cancer" or "non-cancer." The remaining columns show various metrics for each class, including precision, recall, and mean Average Precision (mAP) at different IoU thresholds. This table serves as a record of the model's performance during both training and validation, allowing you to assess its progress and determine whether it is working optimally for the skin cancer detection task. Overall, this table is a record of how well the model is performing during training and validation across different epochs. It helps in assessing whether the model is improving, overfitting, or converging to a suitable solution for the skin cancer detection task. The losses and metrics provide valuable insights into different aspects of model performance, such as object localization and classification accuracy.

A. Confidence curve

The YOLO model assigns a confidence score to each detected object, indicating the level of confidence that the object has been accurately identified. This score is often used to remove detections with low confidence and enhance the precision of the model. The figure is a result of this process.
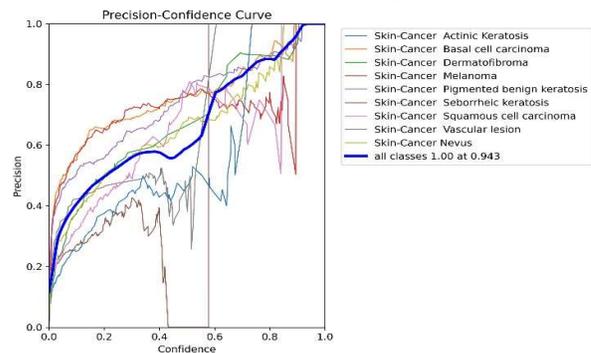

Figure 4.2 Confidence curve

B. Confusion Matrix

1) Non-Normalized Confusion Matrix

In an unnormalized confusion matrix, the values in each cell represent the raw number of predictions made by the model. The matrix provides the actual counts of true positives (TP),

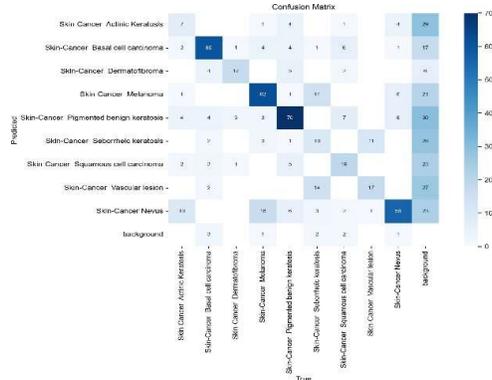true negatives (TN), false positives (FP), and false negatives (FN).

Figure 4.3 Unnormalized Confusion Matrix

2)   Normalized Confusion Matrix

A normalized confusion matrix displays the proportion or percentage of predictions in each cell relative to the total number of instances in each class. This normalization makes it useful when comparing models across datasets with varying class distributions.
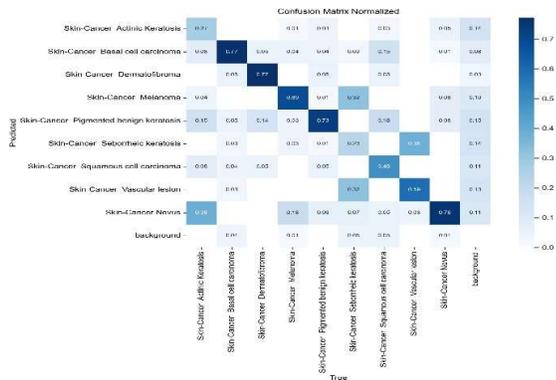

Figure 4.4 Normalized Confusion Matrix
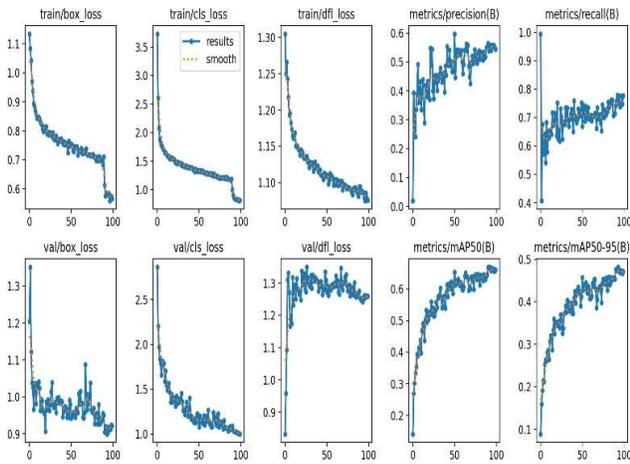
C.   Optimizations

Figure 4.5 Overall Graphical Representation

V.   CONCLUSION AND FUTURE ENHANCEMENT

The development of an advanced intelligent system that specializes in identifying and categorizing different types of skin cancer, an essential area within healthcare diagnostics. The harnesses of the system is state-of-the-art technology, particularly the YOLOv8 computer vision-based object detection algorithm, known for its effectiveness in medical imaging and pathology recognition. The primary objective was to enhance the system's recognition and classification of diverse skin cancer lesions through the advanced capabilities of this algorithm. The research was based on meticulous training using a diverse and comprehensive skin cancer dataset, curated and annotated using robust tools to ensure that our model could distinguish between various skin cancer types by exposing it to a wide range of images. the development process was refined, including rigorous fine-tuning and optimization of the YOLOv8-based model, resulting in outstanding performance metrics, including precision, recall, and F1 score. These measures are crucial to ensure the reliability and efficacy of skin cancer detection and classification. The intelligence of the system is a testament to the successful integration of cutting-edge technology with dermatological diagnostics, resulting in a powerful tool that can accurately diagnose skin cancer early. The implications of such a system extend beyond dermatology, with the potential to influence advancements in medical imaging and contribute to improved patient outcomes in the broader landscape of healthcare. The study leads to assess the effectiveness of AI-based techniques such as dermoscopy, optical coherence tomography (OCT), and reflectance confocal microscopy (RCM). The results reveal that certain AI algorithms exhibit equivalent or superior performance to dermatologists in detecting melanoma, particularly when analyzing dermoscopy images. This study emphasizes the potential of AI to boost diagnostic precision, which could have a positive impact on patient outcomes. However, additional research is required to overcome limitations and ensure the dependability and efficacy of AI-driven techniques.

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