DermaGenics - Early Detection of Melanoma using YOLOv5 Deep Convolutional Neural Networks

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***Abstract*—Skin cancer has become one of the most serious kinds of cancer for people in recent years. Melanoma, basal cell carcinoma, and squamous cell carcinoma are all kinds of skin cancer, with melanoma being the most unexpected. Melanoma can be cured if detected in its early stages. Computer vision can be useful in medical imaging and has already been shown in a number of systems. This study calculates how to identify melanoma skin cancer using machine learning and technological tools. A skin lesion image is sent into the system, which is then examined using novel image processing algorithms to infer the existence of skin cancer. By segmenting the picture and assessing the texture, size, and form of the tumor, the lesion image analysis tool checks for the existence of melanoma (a kind of skin cancer). The picture is classified as a malignant lesion of normal skin or melanoma using the derived feature characteristics. In a nutshell, DermaGenics is a web application integrated with the YOLOv5 model that allows users to input stain's photos. The model takes care of it and evaluates if the stain is cancerous or benign.**

***Index Terms*—yolo, image processing, melanoma, neural networks, healthcare, skin cancer, deep learning, machine learning, early detection**

I. Introduction

Skin cancer is the most common type of cancer and is equally fatal to people of all ages. Millions of non-melanoma skin cancers and 132,000 cases of melanoma skin cancer occur each year. As you can see, WHO statistics analyze each case of "cancer" and assume that such separation has an essential purpose. [1] An important element of skin cancer treatment is early detection. A biopsy is used by doctors to identify skin cancer. This treatment examines a suspicious skin lesion to see if it is malignant. This is a painful and time-consuming process. Therefore, we are using computer-aided technology to develop convenient, inexpensive and rapid diagnosis of skin cancer symptoms. The general procedure performed in our system is to capture the image, preprocess it, segment the captured preprocessed image, extract the desired features, and use roboflow and YOLOv5 for the model. An existing traditional machine learning model.

II. Overview

A. Motivation

In the past, detection of melanoma was done using a biopsy. This is the primary strategy used by doctors to diagnose the majority of cancers. Other tests may reveal malignancy, but only a biopsy may provide a definitive diagnosis. The doctor takes a little quantity of tissue for microscopic inspection during the biopsy. It is done in your clinic and takes almost a week to get the correct results to determine a malignant or benign tumor. Therefore, this system saves time in searching for more efficient detection and treatment recommendations. Records are created statistically.

B. Problem Statement

The most common cancer in the world is a relentless disease that affects one in five people by the age of 70. Fortunately, 99% of all cases can be cured if diagnosed and treated early enough. But to stop skin cancer, you have to be aware of it in time. Skin cancer is the most visible type of cancer. Skin cancers, as opposed to malignancies that form within the body, appear on the outside and are frequently visible. This is why skin inspections at home and by dermatologists are so crucial. Early detection helps to save lives. Knowing what to look for in your skin can help you spot cancer early, when it has the best chance of healing, before it becomes harmful, disfiguring, or deadly. For this reason, you can use a state-of-the-art classifier based on a convolutional neural network (CNN) to classify skin cancer images on par to a dermatologist and install a web app on multiple devices to enable lifesaving and fast diagnosis. As far as we know, there is currently no review of the accurate and rapid results of current research in this area of study.

C. Objectives

1) Eliminate the biopsy and create a completely digital system.
2) Save time and make the process much faster.
3) Easy to access.
4) Avoid late detection leading to fatality.
5) Improve accuracy in the result.
6) User-friendly, Convenient interface.

III. Theory

After detailed scrutinization of various IEEE papers mentioned in the references, the following inferences have been drawn:

Most existing melanoma detecting systems are based on YOLOv3 and YOLOv4 models. So, we decided to come up with a system using YOLOv5s as it is new to the market and is quite advanced in comparison to using YOLOv3 and YOLOv4 as it is much faster and better compatible than YOLOv4. [4]

The training time of YOLOv5s as compared to YOLOv4 shows a drastic drop of more than 1200% as cited by roboflow in the Fig. 1. [5]

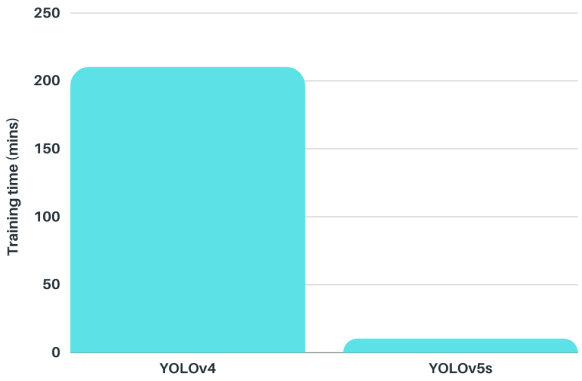

Fig. 1: Training time comparison

Most of the existing systems require high power and energy consumption and hence we implement our system with YOLOv5s that is very efficient and runs on low power equally well. [5]

A. Survey of Existing systems

The system is computerized. It helps in detecting melanoma, but the technology used is not matching up to the expectations for processing speed, computing time as the existing systems are built using ANN with back-propagation algorithm or YOLOv1, YOLOv2, YOLOv3 or YOLOv4. A few systems use CNN classifiers too but no technology can match the speed of YOLOv5 and as of August 2021 there is no paper on this system using the fastest technology available i.e YOLOv5.

B. Limitations and Research Gap

Existing systems have used YOLOv3 / YOLOv4 models which take profuse hours to train a data set as shown in Fig. 2.

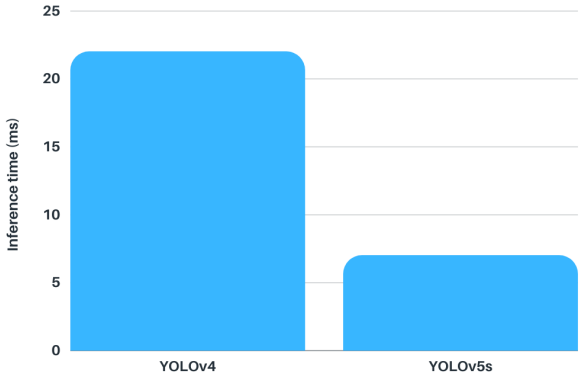

Fig. 2: Inference time comparison

Prevailing models are less power efficient and require robust machines to run.

With Only 83 percent classification accuracy, existing models do not provide substantial results.

After researching, studying and analyzing several IEEE/Springer papers we drew the following inferences:

As mentioned above, a few flaws and drawbacks are present in the research papers. So, to conclude, we found that our proposed system should have all the above present functionalities.

C. Project Contribution

Team 1: Acquiring and Planning Requirements

The plan defines the task of identifying all services provided, describing the facility, and providing the faculty with more details about the laboratory. The problem with this plan begins with the production plan having to meet the user's specifications. In this context, the concentration of facilities for the user department is a major concern. As a result, all fields need to be maintained during development. Planning issues could only include the most important or limited resources. This is where the role of the appropriate requirements collection becomes important. Once the user needs are clear, it will be easier for developers to meet all their needs. He has access to the software because he can see all the resources he needs and can make good plans and cost estimates. Proper planning and recording of requirements enables a highly efficient and robust software.

Team 2: Design and Backend

In software development, design is the most significant and effective aspect. Without the proper design, It is extremely difficult to create software that meets the demands of nearly every user. Therefore, managing the construction part is an

important activity of the organization. Designers need to make the design they create easily understandable to all members of the development team. With proper design, the encoder can properly implement the system development plan. The back-end part, including database management, also plays an important role in each system. Therefore, teams working in this area need to know the correct handling and management of databases and their tools.

IV. YOLO v5s for Early Detection

A. Architecture

The internal architecture of YOLO model consists of three distinct architectural blocks: Backbone, Neck, and Head.

YOLOv5 has several variations of pre-trained models. The difference between them is the trade-off between model size and inference time. The lightweight version of YOLOv5s is only 14MB in size, but on the other side of the spectrum is the 168MB YOLOv5x model which is the most accurate version of the family

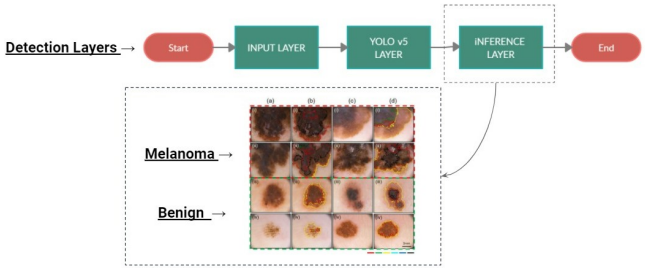

Fig. 3: Modular Diagram of detection layers

B. Algorithm and process design

As of August 2021, there is no paper on the latest launched model YOLOv5s, thus we explain the model used, in comparison with the previous and existing version of YOLOv4 as mentioned below:
YOLOv5 is similar to YOLOv4, with some differences:
YOLOv4 is published in the darknet framework written in C. YOLOv5 is based on the PyTorch framework.
For configuration, YOLOv4 uses .cfg while, YOLOv5 uses .yaml files.[2]

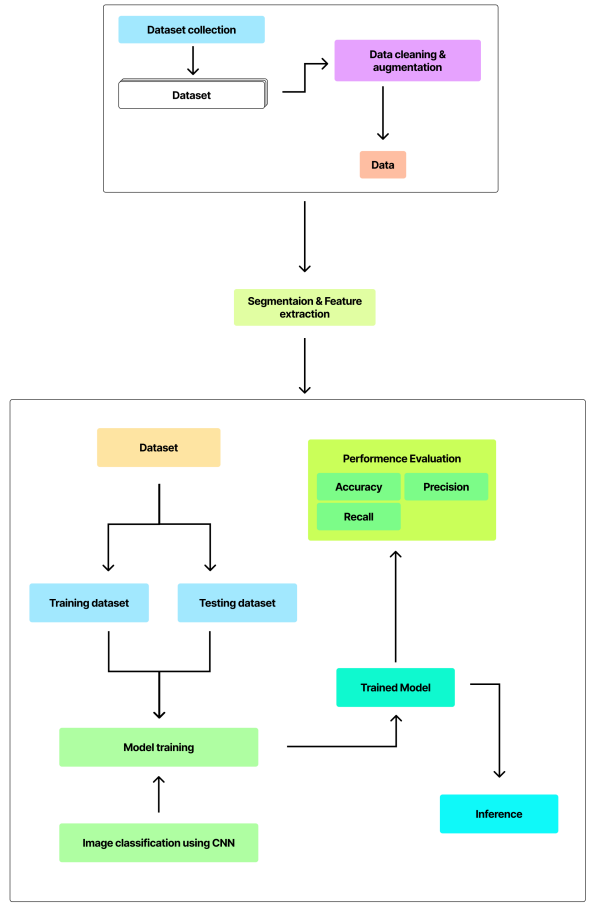

Fig. 4: Block diagram

C. Requirements

Hardware Requirements:

1) Minimum Ryzen 5
2) Nvidia GPU GTX 1060
3) 8 GB RAM
4) SSD/HDD

Softwaree Requirements:

1) Linux/Mac/Windows OS
2) CuDNN 8.1
3) Roboflow
4) Anaconda (Jupyter Notebook) - python 3.8
5) HTML5 / CSS3 / Flutter Web SDK
6) Firebase v8.5.0 / MySQL
7) YOLO v5

V. Results and Evaluations

A. Validation and Verification

During the development process, we evaluated the model to determine if it met the specified requirements. We have split the dataset into training, validation, and testing sets, respectively, to test that the model serves its intended purpose when deployed to the appropriate environment. The following

Figures Fig 5, 6, 7, 8 and 9 show the conclusions drawn from these tests.

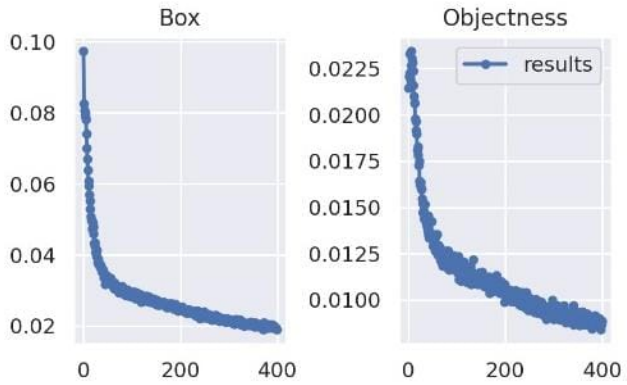

Fig. 5: Box and Objectness

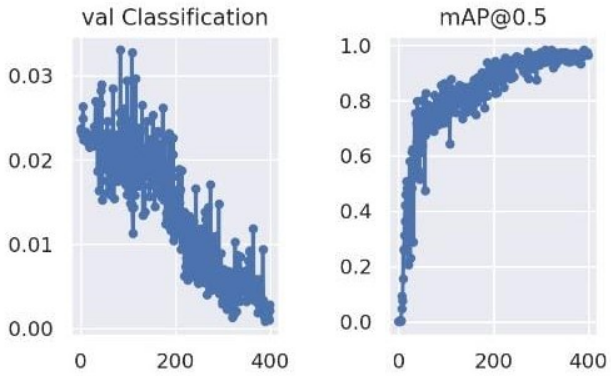

Fig. 6: Val Classification and mAP@0.5

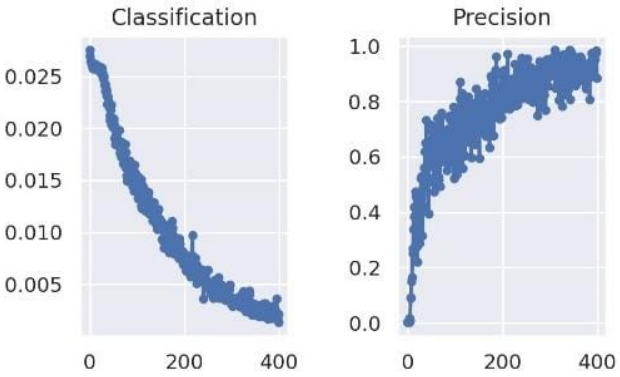

Fig. 7: Classification and Precision

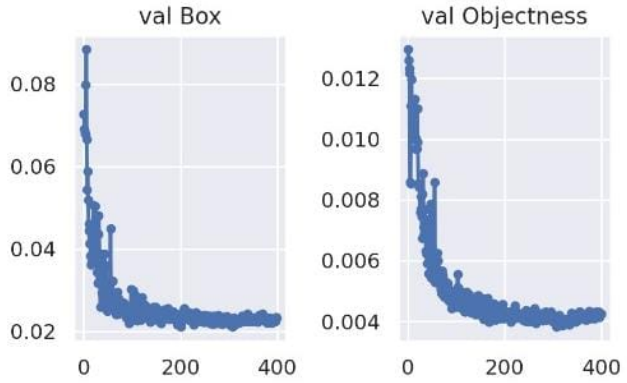

Fig. 8: Val Box and Val Objectness

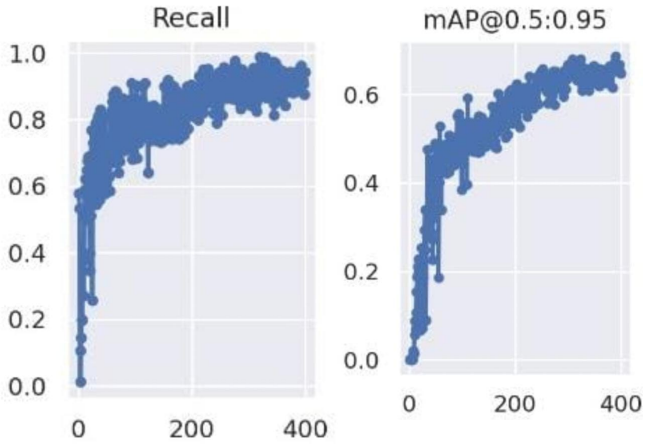

Fig. 9: Recall and mAP@0.5:0.95

B. Analysis

When compared to other filters, conservative filtering produced superior results in the melanoma detection trial. Also, this project concludes that YOLOv5s is the most effective model in comparison to the previous models for the earliest detection.

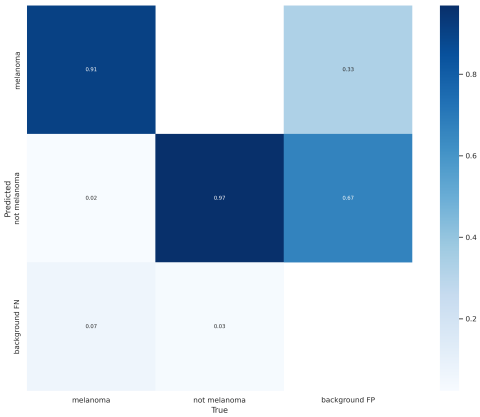

Fig. 10: Confusion Matrix

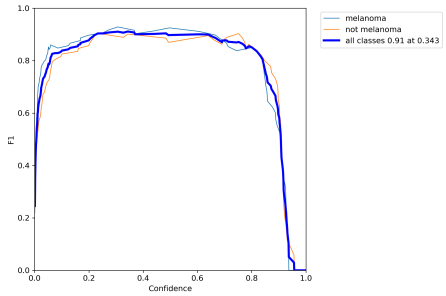

Fig. 11: F1 curve

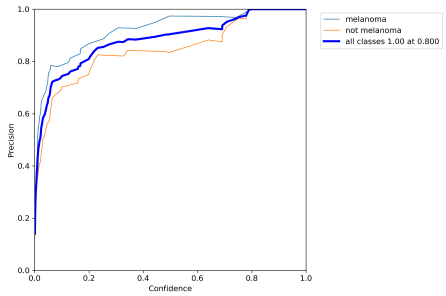

Fig. 12: P curve

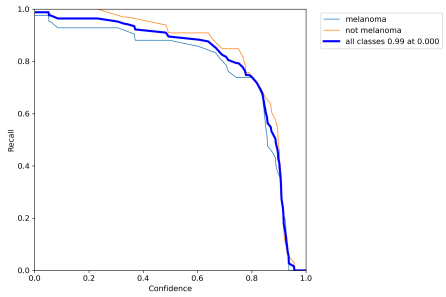

Fig. 13: R curve

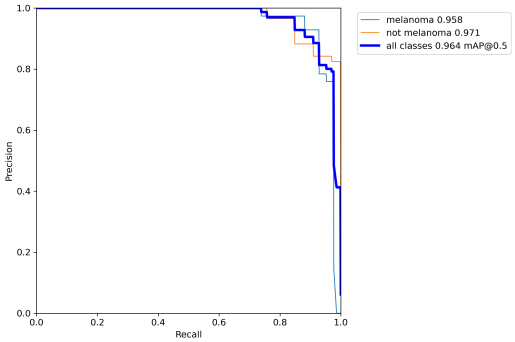

Fig. 14: PR curve

VI. Conclusion and Future Work

Diagnosis of skin cancer melanoma which is done by using our deep learning model is very useful in detecting melanoma at an early stage. With the help of YOLO, an object detection algorithm, our model achieves results on par with conventional biopsy methods. The proposed methodology saves far more time, is convenient, and is cost-free for the patient. Our final delivery comprehensively includes a prediction of melanoma using proper visualization techniques and displayed in a web app with avg precision of 89% for both cases, 93% for melanoma [Fig. 15], and 85% for non-melanoma[Fig. 16] cases respectively.

With a number of hyperparameters, Leaky ReLU as the activation function, adam as an optimizer, we were able to find a lot of metrics in the result.

With future development in the YOLOv5 model, and use of a better optimizer, and an increase in the number PF layers and parameters, we can definitely expect more enhancement and smoother functioning of the model.

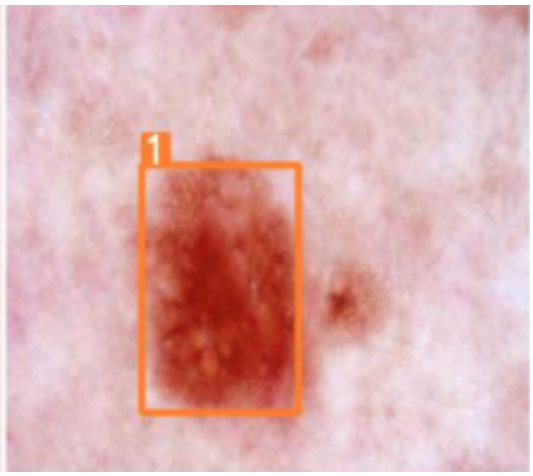

Fig. 15: Melanoma detected

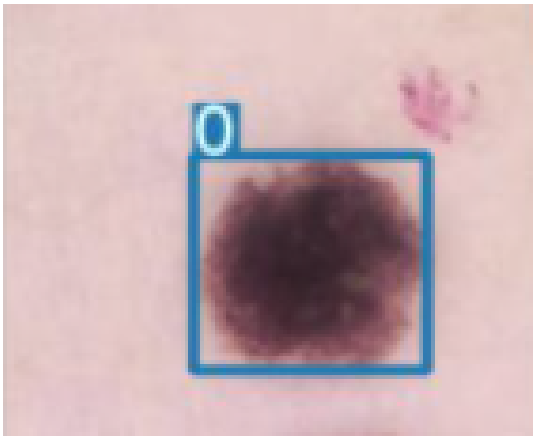

Fig. 16: Melanoma not detected

VII. Acknowledgement

The project of **DermaGenics - Early Detection of Melanoma using YOLOv5 Deep Convolutional Neural Networks** has been a unique experience for us to experience new ventures of enhancing knowledge in areas where we had theoretical information. We gratefully thank our regarded and esteemed mentor Prof. Dr. (Mrs.) Gresha Bhatia of the Computer Department for her helpful direction, supervision, and support throughout the job. Without her support and advice, our plan would not have taken shape.

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