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Development of a Hybrid Medical Softbot for Enhanced Decision Making using AI-tools

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Abstract:- Health is wealth. The maintenance of health is of paramount importance. Due to increasing environmental decay, human health is threatened and therefore requires maintenance. Healthcare providers are few in number and therefore may not be able to cater for everyone. They tend to get fatigued because of the volume of work required on daily basis. This terribly affects their decision making and may lead to death as a result of wrong diagnosis or recommendations. This is the motivation behind this work; design and implementation of a hybrid medical softbot for enhanced decision making. This work was designed with the aid of machine learning algorithms for image analysis and classification and a rule based system that accepts input in the form of symptoms from user to make expert diagnosis and recommendation. Object oriented analysis and design methodology was employed in the analysis and design phase. The result is a hybrid softbot capable of analyzing and classifying X-ray images and giving expert diagnosis for patients.

Keywords:- *Softbot; Machine Learning; Artificial Intelligence***.**

I. INTRODUCTION

The healthcare industry provides medical services to individuals who are sick in order to restore their health. These services could be curative, preventive, palliative or rehabilitative. To give these services, the provider should at all times make spot on decisions so as to ensure efficiency. One wrong decision is capable of causing the death of a patient. In other words, decision making is crucial in the provision of medical services to ailing individuals.

As far as man ages every day and the environment degrades on daily basis, the possibility of health deterioration would continue to increase. This implies that the need for healthcare professionals will continue to be on the increase. Most often, the ratio of healthcare professionals to ailing individuals is overwhelmingly very low. This leads to fatigue on the part of the healthcare professionals which could in turn affect the quality of services they are supposed to render. A fatigued healthcare provider like a doctor could make wrong diagnosis while reading an x-ray image and of course chart a different treatment for the patient.

To mitigate against poor decision making, the healthcare industry embraced the 21st century industrial revolution of using artificial intelligence (AI) tools to assist healthcare professionals to make accurate decisions. Lee (2019) posited that hospitals all over the world are aggressively deploying digital technologies like artificial intelligence, machine learning (ML), smart sensors and robots as well as internet of things (IoT) to improve the quality of healthcare and also make operations efficient especially in countries with stable economies. Safavi and Kalis (2019) noted that AI has had a tremendous impact in the world by increasing throughput which is evidenced by the overwhelming patronage it now enjoys. They also opined that by 2026, AI-based applications could save up to $150 billion annually in savings.

AI-based applications have the capability to learn quickly, all aspects of human life with healthcare inclusive. This implies that, with the aid of AI based technologies, healthcare professionals now have a companion to help to make decisions. Rigby (2019) noted that AI technologies can diagnose skin cancer better and more accurately than a professional dermatologist owing to the fact that their analysis is based on the knowledge acquired from a large body of knowledge and data. Miyashita and Brady (2019) worked on the ability of AI based technologies to analyze patients' data remotely in real time. The reason behind this is to reduce the influx of patients into the hospital. To achieve this, the discharged patient was fitted a wifi enabled armband for the monitoring of the patient's vital signs; respiratory rate, oxygen levels, pulse, blood pressure and body temperature. With this, the expensive home visit was reduced by 22%.

AI tools are built to reduce errors in the healthcare sector. Errors are by far the most threatening factor of a patient's health restoration. Taylor (2019) reported that diagnostic errors account for 60% of all medical errors about 40,000 to 80,000 deaths each year in US hospitals. Given the success AI based solutions have enjoyed, these errors would reduce to the barest minimum once deployed.

Another AI-based tool that is of interest is the rule based system. Here, expert knowledge are encoded into the system in order to provide expert diagnosis. Leveraging on these powerful AI tools, a softbot is designed to enhance decision making in the healthcare industry.

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II. LITERATURE REVIEW

Qilong and Xiaohong (2018) noted that extracting image feature points and classification method are the key to content-based image classification. They extracted image points using SIFT (scale invariant feature transform) algorithm and then clustered the features with K-means clustering algorithm and then bag of work (BOW) of each image constructed. They finally used SVM classifier to classify the images. The experiment yielded an accuracy of 90%.

Sevani et al (2020) worked on medical diagnostics in healthcare industry using a fuzzy approach. They applied the fuzzy inference system within medical diagnostic system so that the uncertainty of diagnostic process can be minimized. A knowledge base was developed based on a physician's experience, containing thirteen (13) symptoms and eleven (11) rules. Then, a web-based platform was designed as a media for physician and or patient to perform diagnostic process. Thirdly, an evaluation of the proposed system was conducted by using blackbox testing, white box testing and error measurement via confusion matrix. The study found that by applying triangular membership function, mamdani inference engine, and de-fuzzification centroid, the system was able to differentiate between typhus and diarrhea.

Bhattacharya et al (2021) worked on deep learning and medical image processing for coronavirus (COVID-19). They x-rayed some concerns in the use of deep learning ranging from unavailability of large datasets with high quality images for training. They posited that synthesizing the data collected from varied sources could be integrated together. The majority of state of the art DL models are trained for 2D images. However CT and MRI are usually 3D and hence add an additional dimension to the existing problem since the conventional DL models are not adjusted this, experience plays a major role when DL models are implemented on these images. The non-standardized process of collecting image data is one of the major issues in medical image processing. It is important to understand that with the increase in data variety, the need of larger datasets arise to ensure the DL algorithm generates robust solutions. The best possible way to resolve this issue is the application of transfer learning which makes pre-processing efficient and eliminates scanner and acquisition issues.

Masri et al (2019) described rule based systems as computer programs based on technologies established by artificial intelligence research which expresses some characteristics of human knowledge and expertise to perform tasks that are normally done by human experts. They noted some important tools for building RBS like simpler level 5subject (SL5) object and C language integrated production system (CLIPS).

An, Rahman, Zhou and Kang (2023) reviewed comprehensively, machine learning in healthcare industry: classification, restrictions, opportunities and challenges. They noted that medical data have been used to dictate diseases and identify patterns. They made a case on the importance of using machine learning algorithms to improve time series healthcare metrics for heart rate data transmission (accuracy and efficiency). They opined that healthcare industry could undergo a variety of technological revolutions owing to machine learning. These revolutions may include among other things; precision in diagnosis, assistance in finding patterns/trends in patients' data and also to simplify administrative processes. They however frowned at some of the difficulties in healthcare sector that affect machine learning like data privacy, ethical issues and the rigorous validation and regulation processes.

III. METHODOLOGY

An image dataset from kaggle, ChestX-Det-dataset was used for this analysis. 70% of the dataset was used for training while 30% was used for testing. RESNET50 was used for feature extraction while tensorflow and openCV were used as the framework for the model learning development and computer vision library respectively. Support vector machine (SVM), a machine learning technique was used for image classification. Medical experts also provided various symptoms and diagnoses for forming the rules for common diseases for the rule based system. Object oriented analysis and design methodology was employed to model software objects after real world objects. The performance metrics used for this work were accuracy, precision, recall and F1.

IV. ANALYSIS

- Analysis of Existing System: When a patient arrives a hospital, the nurse checks and records the patient's vital signs before the doctor examines the patient. The doctor through the examination determines whether the patient is given recommendation to take certain drugs or be subjected to further tests at the laboratory. The result of the test is checked and the doctor interprets the result (whether normal test or x-ray) and gives recommendations. This happens at any time even if the doctor has been working all day. This could lead to errors.
- Analysis of the Proposed System: This is a hybrid form of the existing system where the doctor now has a companion in the form of a medical softbot. This medical softbot is made of two powerful AI tools; the support vector machine (SVM) and the rule based system. The rule based system is used to check common diseases using the symptoms as input while the SVM is used to classify the x-images.

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V. SYSTEM DESIGN AND IMPLEMENTATION

A softbot was designed that has the capability of using support vector machine to classify images and a rule based system that takes symptoms as input and gives diagnosis and recommendations. The image part requires that the user inputs the image into the system. RESNET50 was used to extract the required features and the classification was done by support vector machine. For the rule based system, the knowledge of the experts was used to form the rules.

Some of the images used for the training are shown in figures 1.0 through 1.4.

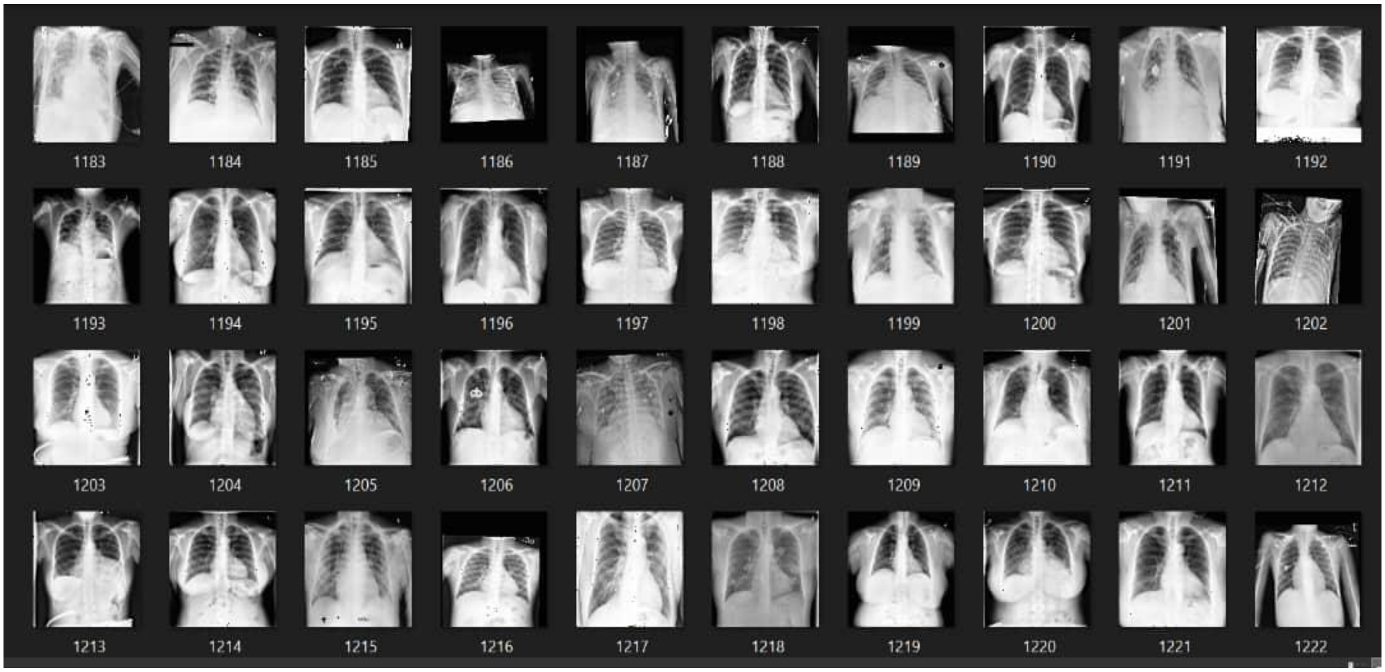

Fig 1: First 40 X-Ray Images of Cardiomegaly Dataset

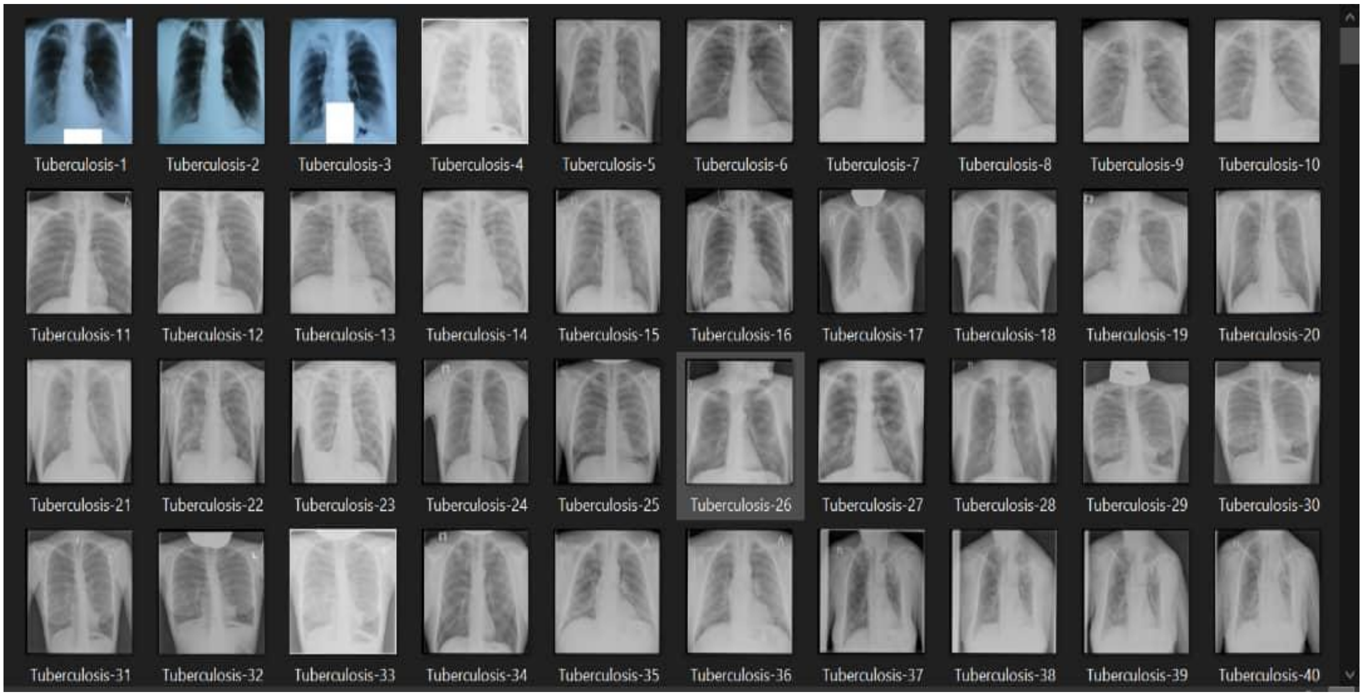

Fig 2: X-Ray Images of Tuberculosis Dataset

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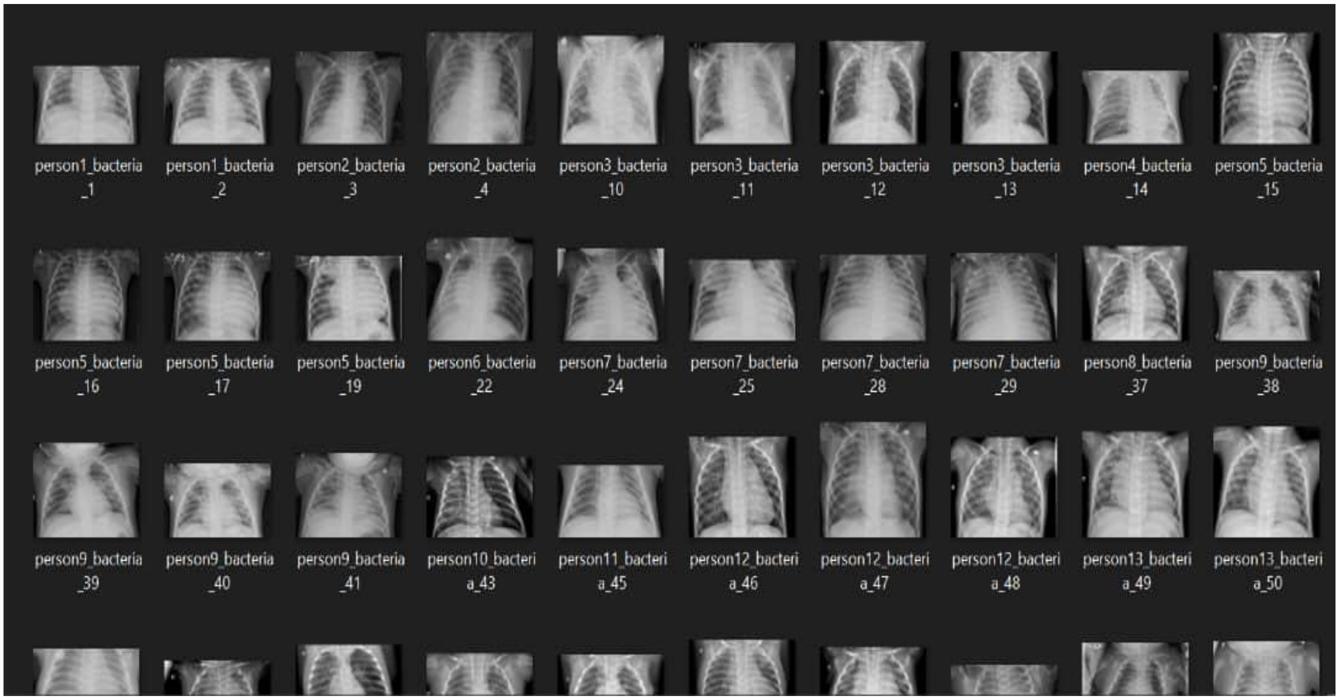

Fig 3: first 40 X-Ray Images of Pneumonia Dataset

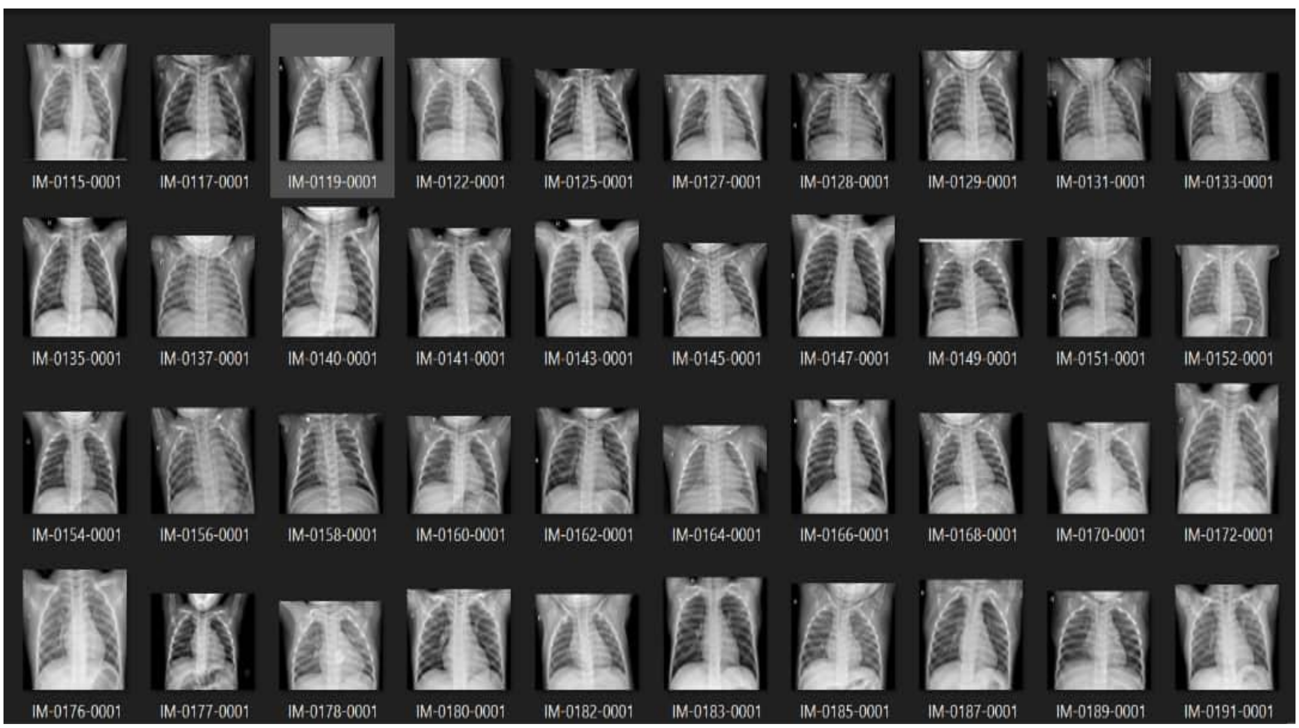

Fig 4: First 40 X-Ray Images of Normal Dataset

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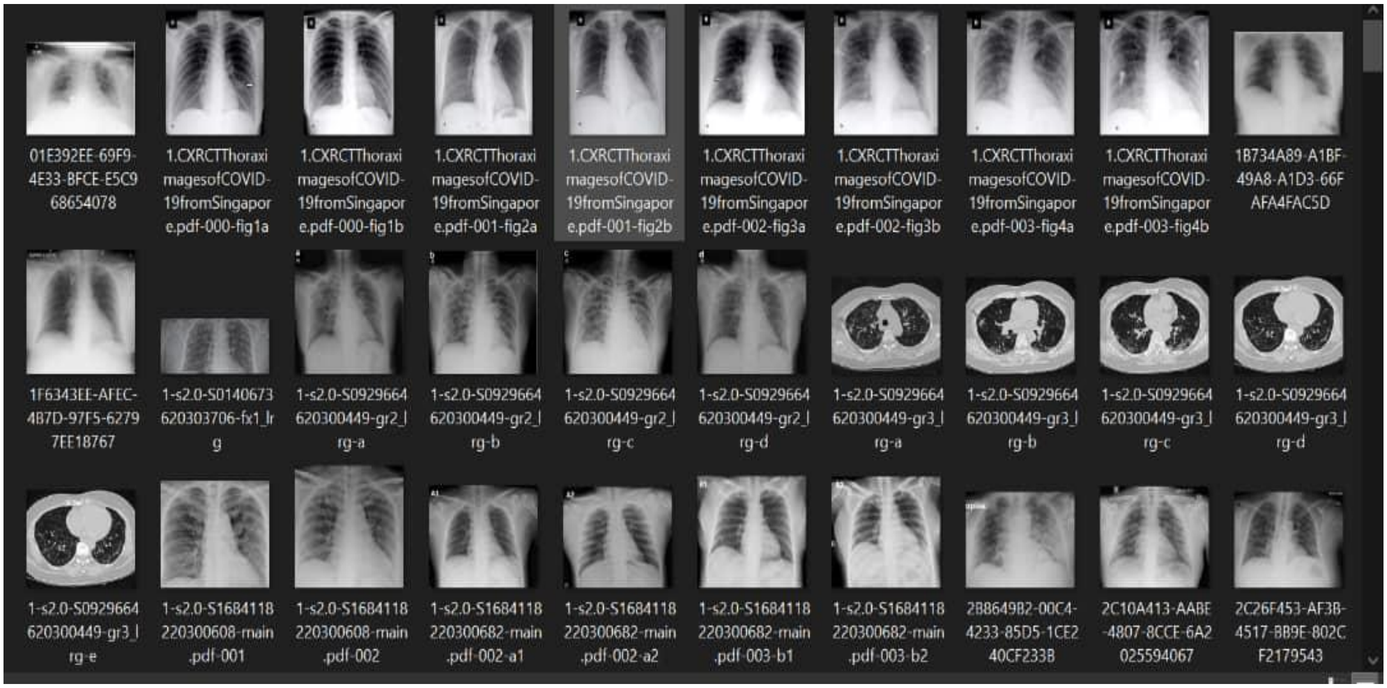

Fig 5: First 30 X-Ray Images of COVID Dataset

VI. PERFORMANCE EVALUATION

Evaluation: The trained model is then evaluated using a validation dataset to assess its performance. Evaluation metrics such as accuracy, precision, recall, and F1 score are used to assess the model's performance.

```
y_pred_svm = svm_clf.predict(X_test)

# Calculate and print classification report
svm_classification_report = classification_report(y_test, y_pred_svm)
print("SVM Classification Report:\n", svm_classification_report)

# Calculate and print precision score, recall score, and F1-score
svm_precision = precision_score(y_test, y_pred_svm)
svm_recall = recall_score(y_test, y_pred_svm)
svm_f1_score = f1_score(y_test, y_pred_svm)
svm_accuracy = svm_clf.score(X_test, y_test)
print("SVM Precision Score:", svm_precision)
print("SVM Recall Score:", svm_recall)
print("SVM F1 Score:", svm_f1_score)

print('SVM ACCURACY: ', svm_accuracy)
# Calculate and print confusion matrix
svm_confusion_matrix = confusion_matrix(y_test, y_pred_svm)
print("SVM Confusion Matrix:\n", svm_confusion_matrix)
```

Fig 6: Model Evaluation

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```
SVM Classification Report:
              precision    recall  f1-score   support

Cardiomegaly       1.00      0.97      0.98       255
       Covid       0.94      0.90      0.92        67
      Normal       0.96      0.97      0.96       220
   Pneumonia       0.97      0.99      0.98       244
Tuberculosis       0.98      1.00      0.99       148

    accuracy                           0.97       934
   macro avg       0.97      0.96      0.97       934
weighted avg       0.97      0.97      0.97       934

Accuracy: 0.97
SVM Precision Score: 0.9734124993225587
SVM Recall Score: 0.9732334047109208
SVM F1 Score: 0.9731677665510096
PS C:\Users\USER\Desktop\hybrid>
```

Fig 7: SVM Classification Report

VII. CONCLUSION

The design of a softbot which leverages on the power of AI tools for enhanced decision making in the healthcare industry would be a big relief to healthcare professionals who work tirelessly to provide medical care. With the use of SVM classifier on images, an accuracy of 97% was got while the rule based system would provide expert diagnoses for common ailments from expert knowledge.

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