COVID-19 DETECTION

Project report submitted in partial fulfillment of the requirement for the degree of Bachelor of Technology
In
Computer Science and Engineering and Information Technology

By
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Under the supervision of
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To

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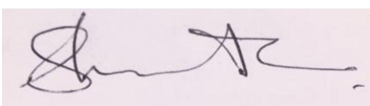
Certificate

Candidate's Declaration

I hereby declare that the work presented in this report entitled "Covid-19 Detection" in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering/Information Technology submitted in the department of Computer Science & Engineering and Information Technology, Jaypee University of Information Technology Waknaghat is an authentic record of my own work carried out over a period from July 2020 to December 2020 under the supervision of Dr. Aman Sharma (Assistant Professor, Computer Science &Engineering Department).

The matter embodied in the report has not been submitted for the award of any other degree or diploma.



(Student Signature)
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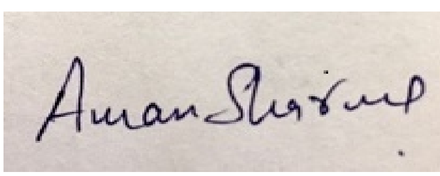
This is to certify that the above statement made by the candidate is true to the best of my knowledge.



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Supervisor Name: Dr. Aman Sharma
Designation: Assistant Professor (Grade-II)
Department name: Computer Science and Engineering and Information Technology

Dated:

ACKNOWLEDGEMENT

I want to take this chance to thank almighty for blessing me with his grace and taking my job to a successful culmination. We owe our profound gratitude to our project supervisor, Dr. Aman Sharma who took keen interest and guided us all along in my project work titled - “Covid-19 Detection” till the completion of our project by providing all the necessary information for developing the project. The project development helped us in research and we got to know a lot of new things in our domain. We are really thankful to him.

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ABSTRACT

The sudden rise in covid-19 cases is affecting healthcare system around the world. But the limited testing facility causes concern because it will put lot of pressure on medical infrastructure. Because the limited inventory of testing kits are available it become difficult for us to test each patients with the disease. The tests which are happening have long testing and limited sensitivity. Detecting possible COVID-19 infections on Chest X-Ray may help quarantine high-risk patients while test results are awaited. X-Ray machines are already available in most hospitals, and with the newest X-Ray machines already digitized, there is no transportation time involved for the samples either. During this project, we propose the deployment of chest X-Ray to prioritize the choice of patients for further RT-PCR testing. This might be useful in an inpatient setting where the present systems are struggling to make your mind up whether to stay the patient in the ward together with other patients or isolate them in COVID-19 areas. It would also help in identifying patients with a high likelihood of COVID-19 with a false negative RT-PCR who would wish to repeat testing. Further, we propose the deployment of recent AI techniques to detect the COVID-19 patients automatically using X-Ray images, particularly in settings where radiologists don't seem to be available and help make the proposed testing technology scalable. We present COVID-19 AI Detector, a unique deep neural network-based model to triage patients for appropriate testing. On the openly available covid chest x-ray dataset, our model gives 94.4% accuracy with 100% sensitivity for the COVID-19 infection. We significantly improve upon the results of Covid-Net on the identical dataset.

CHAPTER 1
INTRODUCTION

1.1 Introduction

The sudden spike in the number of patients with COVID-19, a new respiratory virus, has put an unprecedented load on healthcare systems across the world. In many countries, healthcare systems have already been overwhelmed. There are limited kits for diagnosis, limited hospital beds for admission of such patients, limited personal protective equipment (PPE) for healthcare personnel, and limited ventilators. It is thus important to differentiate which patients with severe acute respiratory illness (SARI) could have COVID-19 infection to efficiently utilize the limited resources. In this work, we propose the use of chest X-Ray to detect COVID-19 infection in patients exhibiting symptoms of SARI. Using our tool one can classify a given X-Ray in one of the four classes: normal, bacterial pneumonia, viral pneumonia, and COVID-19 pneumonia. The use of X-Ray has several advantages over conventional diagnostic tests:

- X-ray imaging is much more widespread and cost-effective than conventional diagnostic tests.
- Transfer of digital X-Ray images does not require any transportation from point of acquisition to the point of analysis, thus making the diagnostic process extremely quick.
- Unlike CT Scans, portable X-Ray machines also enable testing within an isolation ward itself, hence reducing the requirement of additional Personal Protective Equipment (PPE), an extremely scarce and valuable resource in this scenario. It also reduces the risk of hospital-acquired infection for the patients.

The main contribution of this work is in proposing a novel deep neural network-based model for highly accurate detection of COVID-19 infection from the chest X-Ray images of the patients. Radiographs in the current setting are in most cases interpreted by non-radiologists. Further, given the novelty of the virus, many of the radiologists themselves may not be familiar with all the nuances of the infection and may be lacking in the adequate expertise to make a highly accurate diagnosis. Therefore this automated tool can serve as a guide for those at the forefront of this analysis.

We would like to re-emphasize that we are not proposing the use of the proposed model as an alternative to the conventional diagnostic tests for COVID-19 infection, but as a triage tool to determine the suitability of a patient with SARI to undergo the test for COVID-19 infection.

1.2 Problem Statement

On October 24, India's test positivity rate stood at 8.76%, a low value by international standards (because the median test positivity rate was around 9.73%). On the same day, India's testing rate was 1380 persons tested per million population, an extremely low value, again, in comparison to other countries of the world (the median testing rate around the world on that date was about 5,897 persons tested per million population). Many people with coronavirus symptoms have struggled to obtain a test nearby in recent weeks. Reports have emerged of people being asked to drive long distances to test centres even when local ones are quiet. The problem is nationwide, with people in Agra being sent to test sites in Noida and Lucknow, people in Solan being sent to Chandigarh, and others in Surrey being sent to the Shimla, despite the need to hop on a bus.

1.3 Objective

In a covid-19 pandemic, we as a society are suffering a lot due to a stressed healthcare system and poor medical infrastructure which has been put on a test due to pandemic. This Pandemic which is originated from China has spread all over the world like a wildfire. And due to the unplanned and sudden impact on the medical system has got everyone worry. Our objective is to make a cheap testing system that is available for everyone in the furthest of the corner. The project that we are building is very cheap and reliable. Its deployment will help billions of people around the world.

1.1 Methodology

In this project, we address the difficult issue of choice help in mechanized Covid-19 identification dependent on picture information in Electronic-healthcare system. It is to be noticed that some Covid-19 side effects can be comparable to the indications of another irresistible infection, for example pneumonia, anyway there is a reasonable distinction between these two sicknesses as known in the field of medication. Consequently, it is huge to have the option to recognize Covid-19 cases from pneumonia cases while leading robotized identification. In view of this foundation, we characterize our concern as follows. Given chest X-Ray pictures, characterize them as being Covid-19 positive, pneumonia positive or ordinary. Provide the characterization with the end goal that pictures can't cover and should just find a way into one class each The information hotspot for our work is ImageNet, which has openly accessible chest X-Ray pictures on these two infections, just as expected X-Rays, for example those of individuals who tried negative for both these infections.

1.5 Organization

This pre-named information with satisfactory conclusion filling in as the idea of rightness, frames the preparation information in our concern. As such, the named chest X-Ray pictures for Covid-19 and pneumonia permit us to separate between the two and subsequently intend to get exact grouping for Covid-19 by learning by means of existing information. Picture information on chest X-Rays in open storehouses when all is said in done is immense, going from gigabytes to higher requests. It is likewise mind boggling with critical varieties. Surmisings drawn from the information are significant and should be confirmed with sufficient testing to determine their legitimacy according to clinical finding. Subsequently, this issue manages three of the Vs of enormous information, specifically, volume, assortment and veracity.

CHAPTER 2
LITERATURE SURVEY

Convolutional neural networks with many layers have recently been shown to attain excellent results on many high-level tasks like image classification, object detection and more recently also semantic segmentation. Particularly for semantic segmentation, a two-stage procedure is commonly employed. Hereby, convolutional networks are trained to produce good local pixel-wise features for the second step being traditionally a more global graphical model.

Anastasios Doulamis, Nikolaos Doulamis, Klimis Ntalianis, and Stefanos Kollias: Proposed an unsupervised video object (VO) segmentation and tracking algorithm supported an adaptable neural-network architecture. The proposed scheme comprises 1) a VO tracking module and 2) an initial VO estimation module. Object tracking is handled as a classification problem and implemented through an adaptive network classifier, which provides better results compared to standard motion-based tracking algorithms. Network adaptation is accomplished through an efficient and cost-effective weight updating algorithm, providing a minimum degradation of the previous network knowledge, and taking into consideration the present content conditions. A retraining set is made and used for this purpose supported initial VO estimation results. Two different scenarios are investigated. the primary concerns the extraction of human entities in video conferencing applications, while the second exploits depth information to spot generic VOs in stereoscopic video sequences. face body detection supported Gaussian distributions is accomplished within the first scenario, while segmentation fusion is obtained using color and depth information within the second scenario. A decision mechanism is additionally incorporated to detect time instances for weight updating. Experimental results and comparisons indicate the great performance of the proposed scheme even in sequences with complicated content (object bending, occlusion).

Bharath Hariharan, Pablo Arbel´aez, Ross Girshick, and Jitendra Malik:

Detect all instances of a category in a picture and, for every instance, mark the pixels that belong thereto. They call this task Simultaneous Detection and Segmentation (SDS). Unlike classical bounding box detection, SDS requires segmentation and not just a box. Unlike classical semantic segmentation, we require individual object instances. They build upon recent work that uses convolutional neural networks to classify category independent region proposals (R-CNN), introducing a unique architecture tailored for SDS. They then use category-specific, topdown figure-ground predictions to refine our bottom-up proposals. They show a 7 point boost (16% relative) over our baselines on SDS, a 5 point boost (10% relative) over the state-of-the-art on semantic segmentation, and state-of-the-art performance in object detection.

Bogdan Alexe, Thomas Deselaers, and Vittorio Ferrari:

Presented a generic objectness measure, quantifying how likely it's for a picture window to contain an object of any class. We explicitly train it to differentiate objects with a well-defined boundary in space, such as cows and telephones, from amorphous background elements, like grass and road. The measure combines in a very Bayesian framework several image cues measuring characteristics of objects, like appearing different from their surroundings and having a closed boundary. These include an innovative cue to live the closed boundary characteristic. In experiments on the challenging PASCAL VOC 07 dataset, we show this new cue to outperform a state-of-the-art saliency measure and therefore the combined objectness measure to perform better than any cue alone. We also compare to interest point operators, a HOG detector, and three recent works aiming at automatic object segmentation. Finally, they present two applications of objectness. within the first, we sample a tiny low number of windows in line with their objectness probability and provides an algorithm to use them as location priors for contemporary class-specific object detectors. As they show experimentally, this greatly reduces the amount of windows evaluated by the expensive class-specific model. In the second application, they use objectness as a complementary score additionally to the class-specific model, which results in fewer false positives. As shown in several recent papers, objectness can act as a valuable focus of attention mechanism in many other applications operating on image windows, including weakly supervised learning of object categories, unsupervised pixel-wise segmentation, and object tracking in video. Computing objectness is very efficient and takes only about 4 sec. per image.

C.P. Town and D. Sinclair:

Demonstrates an approach to content-based image retrieval founded on the semantically meaningful labeling of images by high-level visual categories. The image labeling is achieved by means of a group of trained neural network classifiers that map segmented image region descriptors onto semantic class membership terms. it's argued that the semantic terms provides a good estimate of the salient features which are important for discrimination in image retrieval. Furthermore, it's shown that the selection of visual categories like grass or sky which mirror high-level human perception allows the implementation of intuitive and versatile query composition interfaces and a spread of image similarity metrics for content-based retrieval.

Cl´ement Farabet, Camille Couprie, Laurent Najman, Yann Lecun:

Propose a way that uses a multiscale convolutional network trained from raw pixels to extract dense feature vectors that encode regions of multiple sizes centered on each pixel. the tactic alleviates the need for engineered features and produces a strong representation that captures texture, shape, and contextual information. They report results using multiple post-processing methods to provide the ultimate labeling. Among those, they propose a method to automatically retrieve, from a pool of segmentation units, an optimal set of units that best explain the scene; these units are arbitrary, e.g. they'll be taken from a segmentation tree, or from any family of over-segmentations.

Clément Farabet, Camille Couprie, Laurent Najman and Yann LeCun:

Proposed scene parsing strategy here beginnings by figuring a tree of sections from a chart of pixel dissimilarities. All the while, a bunch of thick component vectors is figured which encodes locales of various sizes fixated on every pixel. The component extractor is a multiscale convolutional network prepared from crude pixels. The component vectors related with the fragments canvassed by every hub in the tree are amassed and taken care of to a classifier which produces a gauge of the appropriation of item classes contained in the fragment. A subset of tree hubs that cover the picture are then chosen to expand the normal "immaculateness" of the class disseminations, consequently expanding the general probability that each fragment will contain a solitary article. The convolutional network highlight extractor is prepared start to finish from crude pixels, reducing the requirement for designed highlights. Subsequent to preparing, the framework is boundary free. The framework yields record exactnesses on the Stanford Background Dataset (8 classes), the Sift Flow Dataset (33 classes) and the Barcelona Dataset (170 classes) while being a significant degree quicker than contending approaches, delivering a 320 × 240 picture marking in under 1 second.

Hongsheng Li, Rui Zhao, and Xiaogang Wang:

Present profoundly proficient calculations for performing forward and in reverse spread of Convolutional Neural Network (CNN) for pixelwise characterization on pictures. For pixelwise arrangement assignments, for example, picture division and article location, encompassing picture patches are taken care of into CNN for foreseeing the classes of focused pixels through forward engendering and for refreshing CNN boundaries by means of in reverse spread. Nonetheless, forward and in reverse engendering was initially intended for entire picture order. Straightforwardly applying it to pixelwise grouping in a fix by-fix filtering way is very wasteful, in light of the fact that encompassing patches of pixels have enormous covers, which lead to a great deal of repetitive calculation. The proposed calculations dispense with all the repetitive calculation in convolution and pooling on pictures by presenting novel d-routinely inadequate pieces. It produces the very same outcomes as those by fix by-fix examining. Convolution and pooling activities with such portions can consistently get to memory and can run productively on GPUs. A small amount of patches of interest can be browsed each preparation picture for in reverse spread by applying a cover to the mistake map at the last CNN layer. Its calculation intricacy is consistent as for the quantity of patches tested from the picture. Tests have shown that our proposed calculations accelerate usually utilized fix by-fix looking over multiple times in both forward and in reverse proliferation. The speedup increments with the spans of pictures and fixes. Source code of GPU usage is fit to be delivered to general society.

The subject of semantic division has seen extensive advancement due to the amazing highlights learned by convolutional neural organizations (CNNs). The current driving methodologies for semantic division misuse shape data by removing CNN highlights from concealed picture districts. This technique presents fake limits on the pictures and may sway the nature of the separated highlights. In addition, the procedure on the crude picture space need to process a large number of organizations on a solitary picture, which is tedious.

Jonathan Long, Evan Shelhamer and Trevor Darrell:

Show that convolutional networks by themselves, prepared start to finish, pixelsto-pixels, surpass the best in class in semantic division. Their key understanding is to assemble "completely convolutional" networks that take contribution of self-assertive size and produce correspondingly-sized yield with proficient deduction and learning. They characterize and detail the space of completely convolutional networks, disclose their application to spatially thick forecast undertakings, and attract associations with earlier models. They adjust contemporary arrangement organizations (AlexNet, the VGG net, and GoogLeNet) into completely convolutional organizations and move their educated portrayals by adjusting to the division task. They at that point characterize a novel design that joins semantic data from a profound, coarse layer with appearance data from a shallow, fine layer to create precise and point by point divisions. Their completely convolutional network accomplishes condition of-theart division of PASCAL VOC (20% relative improvement to 62.2% mean IU on 2012), NYUDv2, and SIFT Flow, while derivation takes short of what one fifth of a second for a regular picture.

Joseph J. Lim C. Lawrence Zitnick Piotr Doll'ar:

Proposed a novel way to deal with both learning and recognizing nearby form based portrayals for mid-level highlights. Their highlights, called sketch tokens, are found out utilizing regulated mid-level data in the structure of hand attracted forms pictures. Patches of human produced shapes are grouped to frame sketch token classes and an arbitrary timberland classifier is utilized for proficient identification in novel pictures. They show our methodology on both top down and base up undertakings. They show cutting edge results on the top-down assignment of shape location while being over 200_ quicker than contending strategies. They additionally accomplish huge upgrades in identification exactness for the base up assignments of passerby and article identification as estimated on INRIA and PASCAL, separately. These additions are because of the integral data gave by sketch tokensto low-level highlights, for example, slope histograms.

Joao Carreira and Cristian Sminchisescu:

Introduced a novel structure for producing and positioning conceivable items theories in a picture utilizing base up cycles and mid-level prompts. The article speculations are spoken to as figure-ground divisions, and are extricated consequently, without earlier information about properties of individual item classes, by tackling a succession of compelled parametric min-cut issues (CPMC) on a normal picture framework. They at that point figure out how to rank the item speculations via preparing a consistent model to foresee how conceivable the portions are, given their mid-level district properties. They show that this calculation fundamentally outflanks the cutting edge for low-level division in the VOC09 division dataset. It accomplishes a similar normal best division covering as the best performing procedure to date, 0.61 when utilizing only the top 7 positioned sections, rather than the full chain of importance in. Their technique accomplishes 0.78 normal best covering utilizing 154 sections. In a partner paper, they likewise show that the calculation accomplishes cutting edge results when utilized in a division based acknowledgment pipeline. Profound Convolutional Neural Networks (DCNNs) have as of late indicated best in class execution in significant level vision errands, for example, picture characterization and item identification. This work unites strategies from DCNNs and probabilistic graphical models for tending to the errand of pixel-level order (additionally called "semantic picture division").

Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy and Alan L. Yuille: Show that reactions at the last layer of DCNNs are not adequately confined for precise item division. This is because of the very invariance properties that make DCNNs useful for elevated level undertakings. They conquer this helpless restriction property of profound organizations by joining the reactions at the last DCNN layer with a completely associated Conditional Random Field (CRF). Subjectively, their "DeepLab" framework can limit portion limits at a degree of precision which is past strategies. Quantitatively, our technique sets the new condition of-craftsmanship at the PASCAL VOC-2012 semantic picture division task, coming to 71.6% IOU precision in the test set. They show how these outcomes can be gotten productively: Cautious organization re-purposing and a novel use of the 'opening' calculation from the wavelet network permit thick calculation of neural net reactions at 8 edges for each second on an advanced GPU. Mohammadreza Mostajabi, Payman Yadollahpour and Gregory Shakhnarovich present a simply feed-forward design for semantic division. They map little picture components (superpixels) to rich element portrayals removed from a succession of settled areas of expanding degree. These areas are acquired by "zooming out" from the superpixel right to scene-level goal. This methodology abuses factual structure in the picture and in the mark space without setting up unequivocal organized expectation components, what's more, consequently stays away from unpredictable and costly derivation. Rather superpixels are arranged by a feedforward multilayer network. Their engineering accomplishes new cutting edge execution in semantic division, acquiring 64.4% normal exactness on the PASCAL VOC 2012 test set.

Ning Zhang et al:

In his paper "Part based R-CNN's for fine grained class discovery" indicated that semantic part confinement can encourage ne-grained arrangement by unequivocally disengaging unobtrusive appearance dierences related with specifc object parts. Techniques for posenormalized portrayals have been proposed, however by and large assume bouncing box explanations at test time because of the trouble of article location. They proposed a model for ne-grained classification that defeats these impediments by utilizing profound convolutional highlights registered on base up area proposition. Their strategy learns entire article and part finders, implements learned mathematical imperatives among them, and predicts a ne-grained classification from a posture standardized portrayal. Investigations on the Caltech-UCSD winged creature dataset conrm that this technique beats cutting edge ne-grained arrangement techniques in a start to finish assessment without requiring a bouncing box at test time.

Pablo Arbeaez, Bharath Hariharau, Chunhui Gu, Saurabh Gupta, Lubomir Bourdev also, Jitendra Malik:

Tended to the issue of portioning and perceiving objects in genuine world pictures, zeroing in on testing explained classifications, for example, people and other creatures. For this reason, they propose a novel plan for district based item identifiers that coordinates proficiently top-down data from checking windows part models and worldwide appearance signs. Their finders produce class-explicit scores for base up locales, and at that point total the votes of different covering competitors through pixel characterization. They assess our methodology on the PASCAL division challenge, and report serious execution as for current driving procedures. On VOC2010, their technique acquires the best outcomes in 6/20 classifications and the best on expressed articles.

Pedro H. O. Pinheiro Ronan:

Propose a methodology comprising of a repetitive convolutional neural organization which permits them to think about a huge info setting, while at the same time restricting the limit of the model. Collobert Scene parsing is a method that comprise on giving a mark to all pixels in a picture as per the class they have a place with. To guarantee a decent visual cognizance and a high class exactness, it is fundamental for a scene parser to catch picture long range conditions. In a feed-forward design, this can be just accomplished by considering an adequately enormous information setting patch, around every pixel to be named. Opposite to most standard methodologies, our strategy doesn't depend on any division strategies, nor any task-explicit highlights. The framework is prepared in a start to finish way over crude pixels, and models complex spatial conditions with low derivation cost. As the setting size increments with the implicit repeat, the framework recognizes and revises its own mistakes. Their methodology yields best in class execution on both the Stanford Background Dataset and the SIFT Stream Dataset, while staying quick at test time.

Philipp Kr¨ahenb¨uhl, Vladlen Koltun:

Most cutting edge procedures for multi-class picture division and marking utilize restrictive irregular fields (CRF) characterized over pixels or picture areas. While district level models frequently include thick pairwise network, pixellevel models are extensively bigger and have just allowed meager diagram structures. The paper considers completely associated CRF models characterized on the total arrangement of pixels in an picture. The subsequent charts have billions of edges, making customary induction calculations illogical. The commitment is a profoundly proficient rough surmising calculation for completely associated CRF models in which the pairwise edge possibilities are characterized by a straight blend of Gaussian bits. Tests shows that thick availability at the pixel level significantly improves division and marking exactness.

Pierre Sermanet David Eigen , Xiang Zhang Michael Mathieu Rob Fergus Yann LeCun:

Present an incorporated system for utilizing Convolutional Networks for order, limitation and location. They show how a multiscale and sliding window approach can be effectively executed inside a ConvNet. They likewise present a novel profound learning way to deal with limitation by figuring out how to foresee object limits. Bouncing boxes are at that point collected as opposed to smothered to expand discovery certainty. They show that various undertakings can be adapted at the same time utilizing a solitary shared organization. This incorporated structure is the victor of the restriction undertaking of the ImageNet Large Scale Visual Acknowledgment Challenge 2013 (ILSVRC2013) and acquired exceptionally serious outcomes for the recognition and characterizations undertakings. In post-rivalry work, they build up another condition of the craftsmanship for the recognition task. At long last, they discharge an element extractor from our best model called OverFeat.

Rainer Lienhart and Axel Wernicke:

Propose a novel strategy for limiting and dividing text in complex pictures and recordings. Text lines are distinguished by utilizing a complex-esteemed multilayer feed-forward organization prepared to recognize text at a fixed scale and position. The organization's yield at all scales and positions is coordinated into a solitary book saliency map, filling in as a beginning stage for applicant text lines. On account of video, these up-and-comer text lines are refined by misusing the fleeting excess of text in video. Confined content lines are then scaled to a fixed tallness of 100 pixels and sectioned into a parallel picture with dark characters on white foundation. For recordings, fleeting excess is misused to improve division execution. Information pictures and recordings can be of any size because of a valid multiresolution approach. In addition, the framework isn't simply ready to find and section text events into huge parallel pictures, but at the same time can follow every content line with sub-pixel exactness over the whole event in a video, with the goal that one content bitmap is made for all examples of that text line. Thusly, their content division results can likewise be utilized for object-based video encoding, for example, that empowered by MPEG-4.

Richard Socher richard, Cliff Chiung-Yu Lin, Andrew Y. Ng, and Christopher D. Manning:

Present a maximum edge structure expectation design dependent on recursive neural networks that can effectively recuperate such structure both in complex scene pictures also as sentences. A similar calculation can be utilized both to give a serious syntactic parser for common language sentences from the Penn Treebank and to outflank elective approaches for semantic scene division, explanation and characterization. Recursive structure is generally found in the contributions of various modalities, for example, common scene pictures or normal language sentences. Finding this recursive structure encourages us to not just distinguish the units that a picture or sentence contains yet in addition how they cooperate to frame a entirety. For division and explanation their calculation acquires another degree of condition of-theart execution on the Stanford foundation dataset (78.1%). The highlights from the picture parse tree outflank Gist descriptors for scene arrangement by 4%.

Ross Girshick:

In 2015 introduced the strategy "Quick R-CNN". In his paper he proposed Fast R-CNN, a perfect and quick structure for object identification. Contrasted with conventional R-CNN, what's more, its quickened adaptation SPPnet, Fast R-CNN trains networks utilizing a perform multiple tasks misfortune in a single preparing stage. The perform multiple tasks misfortune disentangles learning and improves location exactness. In contrast to SPPnet, all organization layers can be refreshed during adjusting. They show that this contrast has viable implications for profound organizations, for example, VGG16, where mAP endures when just the completely associated layers are refreshed. Contrasted with "moderate" R-CNN, Fast RCNN is 9 quicker at preparing VGG16 for discovery, 213 quicker at test-time, and accomplishes a fundamentally higher mAP on PASCAL VOC 2012. Contrasted with SPPnet, Fast R-CNN trains VGG16 3 quicker, tests 10 quicker, and is more precise.

Item discovery execution, as estimated on the accepted PASCAL VOC dataset, has leveled over the most recent couple of years. The best-performing strategies are perplexing outfit frameworks that ordinarily consolidate numerous low-level picture highlights with significant level setting. In this paper, **Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik** propose a basic furthermore, versatile recognition calculation that improves mean normal exactness (mAP) by more than 30% comparative with the past best outcome on VOC 2012—accomplishing a mAP of 53.3%. Their approach joins two key experiences: (1) one can apply high-limit convolutional neural networks (CNNs) to base up district proposition to restrict and portion objects and (2) when named preparing information is scant, regulated pre-preparing for an assistant undertaking, followed by space explicit tweaking, yields a critical presentation help. Since They join district proposition with CNNs, we call our strategy R-CNN: Regions with CNN highlights. We likewise contrast R-CNN with OverFeat, an as of late proposed sliding-window finder in light of a comparative CNN engineering. They find that R-CNN outflanks OverFeat by an enormous edge on the 200-class ILSVRC2013 identification dataset.

Shaoqing Ren et. Al:

Distributed paper on Faster R-CNN, utilizing it for Real-Time Object Discovery with Region Proposal Networks. Best in class object identification networks depend on area proposition calculations to estimate object areas. Advances like SPPnet and Fast R-CNN have diminished the running season of these discovery organizations, uncovering locale proposition calculation as a bottleneck. In this work, they presented a Region Proposal Network (RPN) that offers full-picture convolutional highlights with the recognition organization, hence empowering almost sans cost locale recommendations. A RPN is a completely convolutional network that at the same time predicts object limits and objectness scores at each position. RPNs are prepared start to finish to create excellent locale proposition, which are utilized by Fast R-CNN for recognition. With a basic substituting enhancement, RPN and Fast R-CNN can be prepared to share convolutional highlights. For the extremely profound VGG-16 model, their identification framework has a casing pace of 5fps (counting all means) on a GPU, while accomplishing best in class object identification precision on PASCAL VOC 2007 (73.2% mAP) and 2012 (70.4% mAP) utilizing 300 proposition for each picture.

Shuai Zheng Sadeep Jayasumana, Bernardino Romera-Paredes, Vibhav Vineet, Zhizhong Su,Dalong Du, Chang Huang, and Philip H. S. Torr:

Pixel-level naming assignments, for example, semantic division, assume a focal function in picture understanding. Later approaches have endeavored to bridle the abilities of profound learning methods for picture acknowledgment to handle pixellevellabelling undertakings. One focal issue in this technique is the restricted limit of profound learning methods to depict visual items. To tackle this issue, we present another type of convolutional neural organization that consolidates the qualities of Convolutional Neural Networks (CNNs) and Conditional Random Fields (CRFs)- based probabilistic graphical demonstrating. To this end, Conditional Random Fields as Repetitive Neural Networks is defined. This organization, called CRF-RNN, is then connected as a piece of a CNN to acquire a profound organization that has alluring properties of both CNNs and CRFs. Critically, the framework completely incorporates CRF displaying with CNNs, making it conceivable to prepare the entire profound organization start to finish with the standard back-engendering calculation, maintaining a strategic distance from disconnected post handling strategies for object depiction. The proposed strategy to the issue of semantic picture division, getting top outcomes on the difficult Pascal VOC 2012 division benchmark.

S. Ji and H.W. Park:

Proposed Two-venture picture division calculation, which depends on district coherency for the division of shading picture. The initial step is the watershed division, and the following one is the district consolidating utilizing fake neural networks. Spatially homogeneous districts are acquired by the initial step, yet the areas are over portioned. The subsequent advance consolidations the over divided areas. The proposed technique abuses the luminance and chrominance distinction parts of shading picture to verifv locale coherency. The YUV shading coordinate framework is utilized in this work.

Diagram cut advancement is one of the standard workhorses of picture division since for twofold irregular field portrayals of the picture, it gives all around the world ideal outcomes and there are productive polynomial time usage. Regularly, the arbitrary field is applied over a level apportioning of the picture into non-crossing components, for example, pixels or super-pixels.

Victor Lempitsky, Andrea Vedaldi and Andrew Zisserman:

In the paper they show that if, rather than a level apportioning, the picture is spoken to by a progressive division tree, at that point the coming about energy consolidating unary and limit terms can even now be enhanced utilizing chart cut (with all the relating advantages of worldwide optimality and effectiveness). Because of such induction, the picture gets divided into a bunch of sections that may come from various layers of the tree. They apply this detailing, which they call the arch model, to the undertaking of semantic division where the objective is to isolate a picture into zones having a place with distinctive semantic classes. The tests feature the upside of induction on a division tree (over a level dividing) and show that the advancement in the arch model can deftly pick the degree of division over the picture. Generally, the proposed framework has prevalent division precision on a few datasets (Graz-02, Stanford foundation) contrasted with recently proposed approaches.

CHAPTER 3
SYSTEM DEVELOPMENT

3.1 Experimental Setup

To train the transfer learning models python programming language was used along with Keras and Tenserflow. Keras is a neural network library built on top of Tenserflow and is very simple to use. It provides all the functionality needed for building complicated deep learning models. All the work was done on google colab which is a online platform for running jupyter notebook. Google colab was built to write and execute arbitrary python code through browser.It provides free excess to the computing resources including GPUs.

It allows the user to mount the google drive making it easy to import datasets directly to the notebook. This setup was used along with the set of weights learned by the pre-trained model on ImageNet.

3.1.1 Dataset Description

The dataset used in this experiment contains 940 X-rays images of confirmed Covid cases ,pneumonia and normal(no infection) patients. The dataset is taken from a github repository and contains 435x-ray image of covid patients and 505 x-ray image of Non-covid patients.The data was collected from public sources as well as from hospitals and physicians. Data is evenly distributed but contains a limitation that is not enough images are collected to train the model accurately and with precision. Normal image do not imply that the patients do not have ant other emerging diseases.

To supply the models with enough data we used a technique called data augmentation to increase its volume. Data augmentation is a common process in deep learning which increases the number of samples by creating a new sample by flipping the image, rotating left or right. This is done when there is lack of samples to train the model.

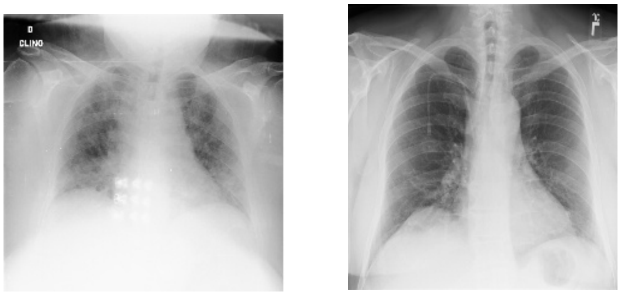


Figure 1: Sample of X-ray images

3.1.2 Performance Metrics

Performance metrics used are as follows:

$$\text{Accuracy}(ACC) = (TP + TN)/n$$

$$\text{Precision}(P) = TP/(TP + FP)$$

$$\text{Recall}(\text{Sensitivity}) = TP/(TP + FN)$$

$$F1-\text{Score} = 2(\text{Precision} * \text{Recall})/(\text{Precision} + \text{Recall})$$

Where TP, TN, FP, FN are true positive, true negative, false positive, false negative samples for each class. Micro average results were also calculated and used to present the classification performance of the models. All metrics were computed every time after changing the number of epochs. Models were trained at 10,100 and 500 epochs to compare the result of each experiments.

Accuracy is a commonly used classification metric which shows how well a algorithm can discriminate the classes in the test set.It is measures as proportion of the predicted correct labels to total number of test cases. Here accuracy means the total accuracy of the model. Precision tells us how many of the true predicted are actually labeled as true. It is the proportion of predicted correct to the total number of labels. Recall tells us how many labeled true are correctly labeled true. It is the proportion of correctly labeled positive to total positive. It is also called true positive rate. F1 score is the harmonic mean of Precision and Recall.

	precision	recall	f1-score	support
0	1.00	0.61	0.76	88
1	0.75	1.00	0.86	101
accuracy			0.82	189
macro avg	0.87	0.81	0.81	189
weighted avg	0.87	0.82	0.81	189

Figure 2: Classification report of Inception V3 model after 10 epoch

3.1.3 Parameter Tuning

There are some common parameters in CNN models. All images were set to 224*224 pixels. The dataset was split into training and testing datasets. Training datasets contained randomly mixed 80% of total data whereas testing dataset had 20% of the remaining data. The training was done with different numbers of epochs(10,100,500) with the batch size of 32. All models were compiled with optimizer as Adams and loss as categorical_cross entropy and the convolution layer were activated by Rectified Linear Unit(ReLU). On top of pre-trained models we added few extra layer to fit the model according to our problem. We added a flatten layer, a dropout layer and a dense layer. Flatten layer help us to convert the data into a 1-dimensional array for inputting into the next layer. Dropout layer helps us to drop some of the neurons randomly while training. A dropout layer of).5 was applied after the flatten layer which will set 50% of the neurons randomly in each epochs . This helps with the problem of overfitting on small training thus creating regular distribution of the weights. All the outputs from this layer act as a input for the dense layer. In dense layer all neurons from previous layer are fully connected to the dense layer. This layer uses softmax activation function classifies image into either Covid or Non-covid. Softmax assigns decimal probabilities to each class in multi-class classification. Finally if probability from softmax is greater than 0.5 then we will declare that Covid with 'probability*100 Covid' else we will declare Non-covid with'1-probability*100 Non-covid'.

Categorical crossentropy compares the distribution of the predicted with the true distribution.True class is encoded with one hot coded vector and close the outputs to the vector less is the loss.

$$CE = -1/N\sum_{i=1}^{N}\log P\,\mathrm{mod}el[yi \in Cyi]$$

Where $P\,\mathrm{mod}\,el[yi \in Cyi]$ is the probability predicted by the model for the i^{th} observation to belong to the c^{th} category.

3.2 Transfer learning with CNNs

Deep learning models require large datasets to be able to perform accurate feature extraction and classification. As we are working on Covid dataset, the work done on this fiekd is minimal and is at very early stage, Therefore, finding a large dataset is very difficult. To solve the problem we can use transfer learming. In transfer learning we can use a pre-trained model with all its parameters and weights. The models are alredy trained with large datasets and are stored. Users can import the pre-trained model and use it to train a new model with smaller dataset.Thus the problem of training a large model with large dataset is eliminated.

Transfer learning can be of two types feature extraction and fine tuning. In feature extraction a new classifier is trained on top of the pre-trained model. Representation learned in pre-trained model are used as such for extracting features from the new samples. The base network already contains generic feature foe classification therefore, there is no need to train the model again. Next method is fine tuning and it increases the performance of the model. We add layers to the already trained model and fine tune the weights of pre-model along with added layers for the new data that is available. Here we will be tuning weights from generic feature map to feature association specially for the given dataset.

In our work, we have fine tuned the CNNs model to identify and classify two classes that are covid and non-covid. The weights used by this pre-trained models are trained on ImageNet. ImageNet is a huge image database containing over 14 million images that are divided int 20,000 categories specially created for image recognition competitions.

We have used VGG19 and Inception V3 models for classifying the images. On top of these we have added a flatten layer, dropout layer with 0.5 and a dense layer with softmax activation layer which will give classify the image to either of the two classes with decimal probability. One the basis of the probability we will figure out its class.

3.2.1 VGG19

VGG19 is a pre-trained deep learning model based on convolution operation. VGG is a successor of AlexNet but was created by different group named Visual Geometry Group at Oxford. It has 16 3*3 convolutional layers , 3 fully connected layer and a softmax layer. In between we also have 5 maxpooling layers which allows us to reduce the dimensionality and down sample an input representation. It makes an assumption about feature contained in the sub-regions binned. The dataset containing image of size 224*224 is fed to the model. Each filter is 3*3 size with stride size of 1. Stride size of 1 and 3*3 filter helps to cover all the areas in the image. Also padding size 1 was used to preserve the original resolution of the image. Maxpooling was performed with stride size of 2 and 2*2 pixel window. Max pooling is followed by ReLU which helps in making the model better by introducinh non-linearity compared to previous version which used tanh or sigmoid activation function. At last three fully connected layer are implemented out of which two have a size of 4096 and the last layer has channel size of 1000 for 1000 way ILSVRC classification. Final layer is softmax layer.This model can can fine tuned and more layers can be added to use this network for other tasks.

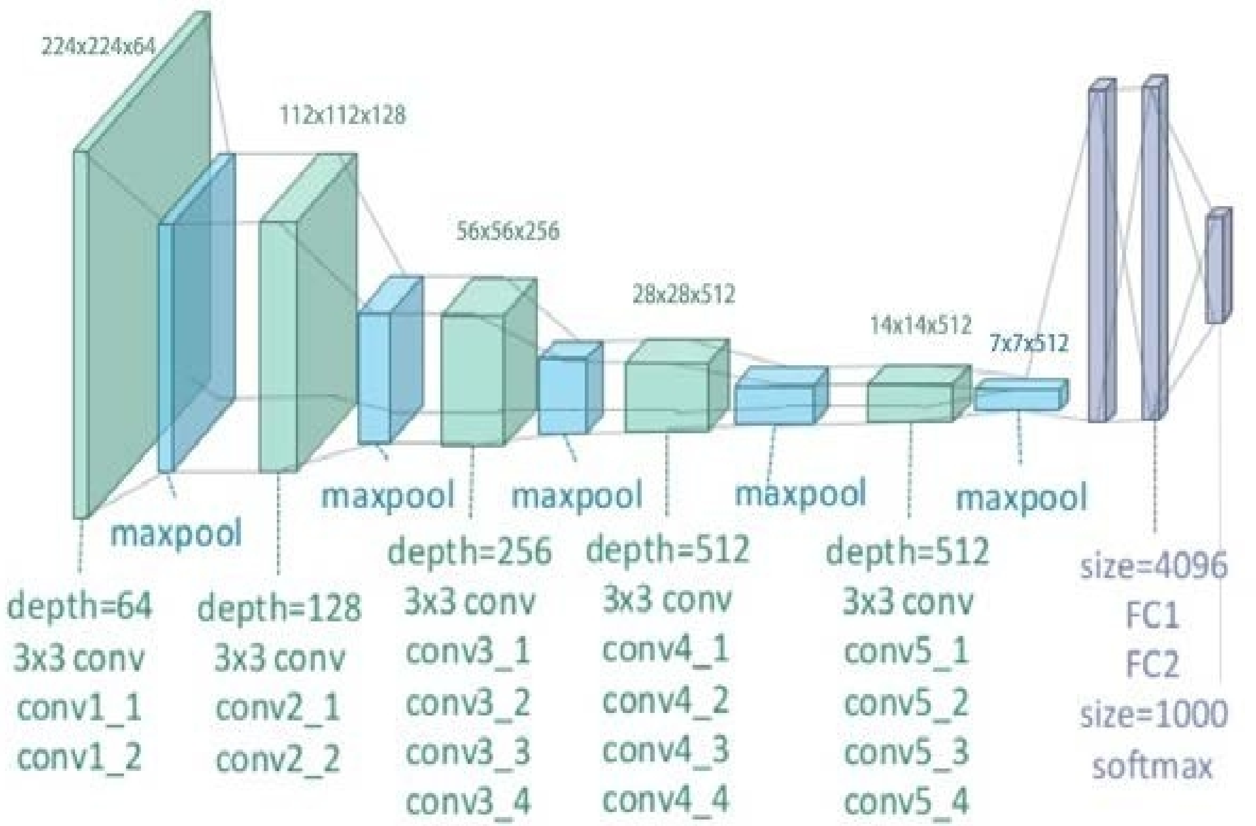


Figure 3: Structure of VGG19 model

3.2.2 InceptionV3

InceptionV3 is a pre-trained model convolution neural network that is 48 layer deep. User can load the pre-trained model which is trained on ImageNet dataset. It is extended network of GoogleNet and was runner up in ILSVRC 2015. InceptionV3 gave a new inception model which concatenates multiple different sized convolutional filter into new filter. This design decreases the number of parameters to trained hence decreasing the computation cost and increasing efficiency. To reduce the computational cost inception model takes the input from previous layer and performs a 1*1 convolution to reduce its size and this is also called bottleneck of the model as it will be the smallest matrix . Followed by 1*1 layer 3*3 and 5*5 convolution filter is put behind the 1*1 convolution filter. This operation reduces the computational cost to 1/10th of the what it would have been if we had used 3*3 or 5*5 convolutional filter directly. We concat all the layers in that are 1*1 filter, max pooling layer with stride 1 followed by 1*1 filter,1*1 filter followed by 3*3 filter and 1*1 filter followed by 5*5 filter. This is the basic inception module and in inception V3 we have differently designed inception modules which have more complex structure. InceptionV3 model uses Inception

Module A,Module B and Module C.The final part consist of average pooling layer, dropout layer, fully connected layer and final softmax layer. There is one side branch and it is called Auxillary Clasifier and what is does is it tries to take input fro one of the hidden layer and predict output in middle rather than at end.

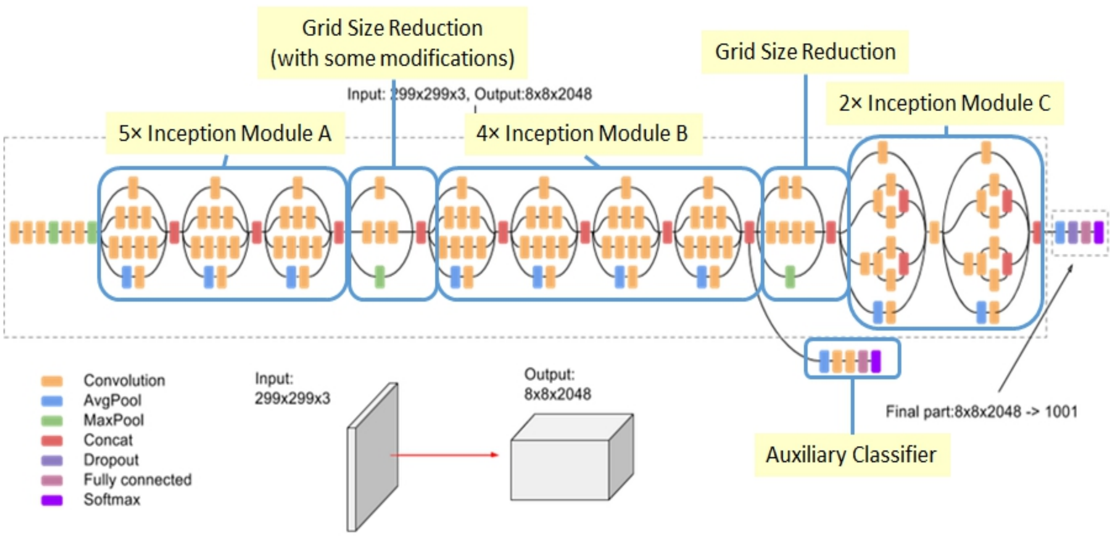


Figure 4: InceptionV3 model

3.3 Model Implementation

To start with we mounted the drive containing the data in google colab jupyter notebook. All the libraries were imported.Pandas was imported to help with reading the datset. Numpy was imported to convert dataframe into arrys. Seaborn and matplotlib were imported as they are the librries that help us to plot graphs. From scikit learn confusion matrix and roc curve were imported to evaluate the model. From Keras many libraries such as Input, Lambda, Dropout, Dense, Flatten, GlobalAveragePool, Model, load_model, VGG19, InceptionV3, preprocess_input, image, ImageDataGenerator were imported. VGG19 and InceptionV3 are pretrained model that will be fine tuned for doing the sepcific task of classifying image into Covid and Non-Covid. Dense, Flatten, Dropout helps us to add dense layer, flatten layer, dropout layer respectively on top of fine tuned pre-trained VGG and Inception model. Glob was imported to grab image from path in the system. cv2 was imported to help us read image files using its functions imread(), it also has function cvtColor() to convert images to RGB format, its resize function was used to convert the image into 224*224 format to match with the input given to the pre-trained models. Labels were prepared for the data and were converted into binary format.

The was splitted into 80% training data 20% testing data. To tacle the problem of having less data we used a method called data augmentation to increase the number of samples. Also data were randomly mixed so as to make the model run accurately for both labels.

For VGG19 model the top layers were not included for performing the task. Its fully connected layer and softmax layer were removed for fine tuning process. On top of VGG19 a flatten layer, a dropout layer with the value of 0.5 was given to set the 50% of neurons randomly so as to prevent overfitting, a dense layer with 2 neurons and soft max activation function were added. While compiling the whole model adam optimizer was used to optimize the model and categorical crossantropy was used as loss function. Total numbers of parameter in the model are around 20 million out of which 50 thousand are trainable parameters and the rest are non-trainable parameters.

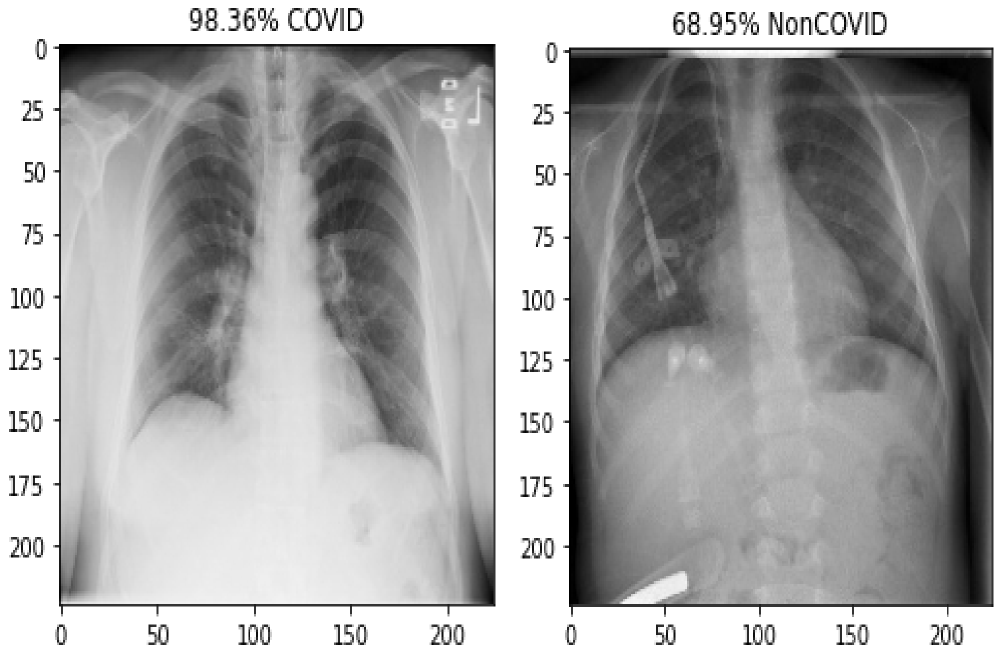


Figure 5: Output of VGG19 model

For inceptionV3 model the top layers were excluded which consists of fully connected layers and softmax activation function. A flatten layer, a dropout layer, a dense layer with softmax function were added on top. The purpose of adding extra layers is to make the full model apapt to the new data set. Total parameters in this model are around 22 million out of which 100 thousand were trainable and rest were non-trainable. The ore-trained weights of the initial convolution layers serve as the backbone of the model and are freezed and only the last convolution layers are trained to convert those extracted features into prediction for the specified classes for the new data set.

Both the models were trained for 10,100,500 epoches. Values of precision, recall, F1 score were recorded each time. Confusion matrix, roc-curve, model accuracy graph for each epoches, model loss graph were also plotted.

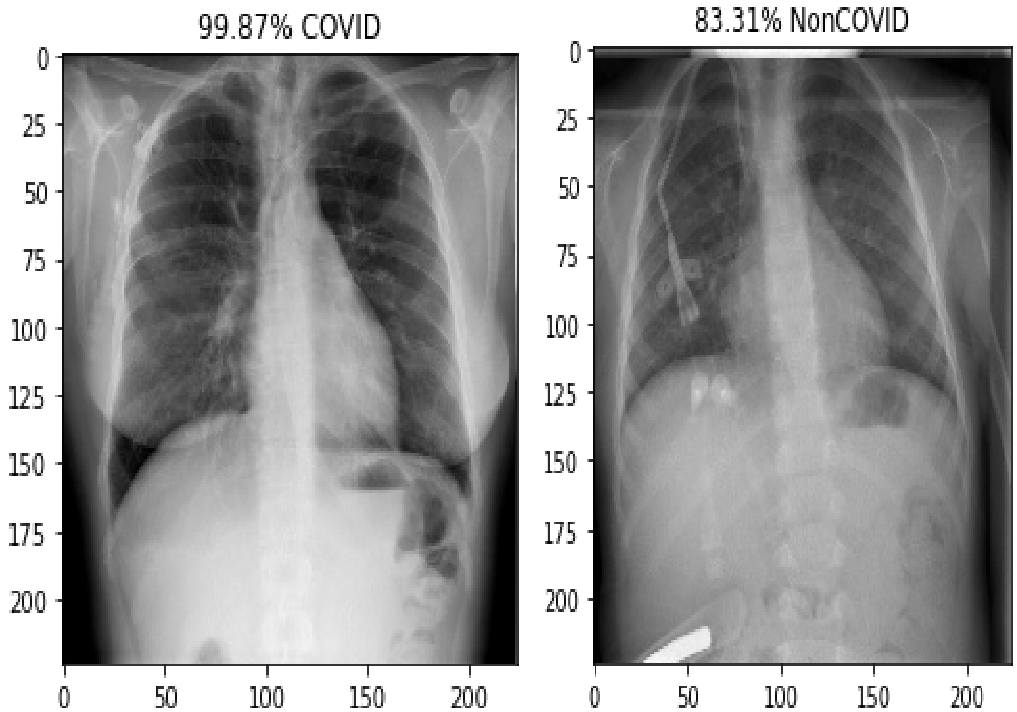


Figure 6: Output of Inception model

Chapter 4

PERFORMANCE ANALYSIS

We haved trained the model with different number of epoch. Therefore all performance analysis are done on all types of models with different number of epochs. The performance of models were evaluated using receiver operating characteristic curve. The area under the curve represents the usefulness of the model. It is plotted between false positive rate and true positive rate.

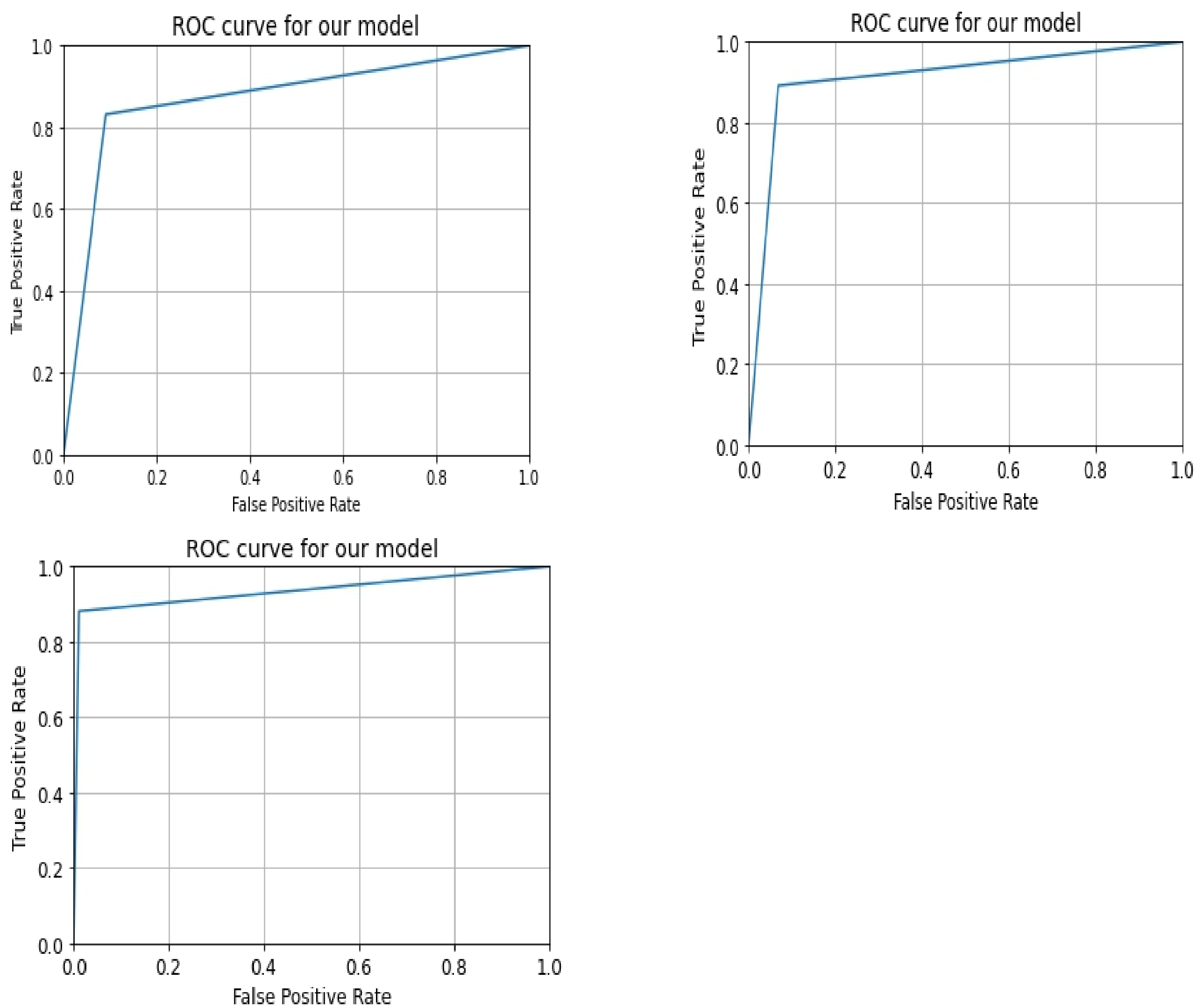


Figure 7: Roc curve for VGG19 a)10 epochs b)100 epochs c)500 epochs

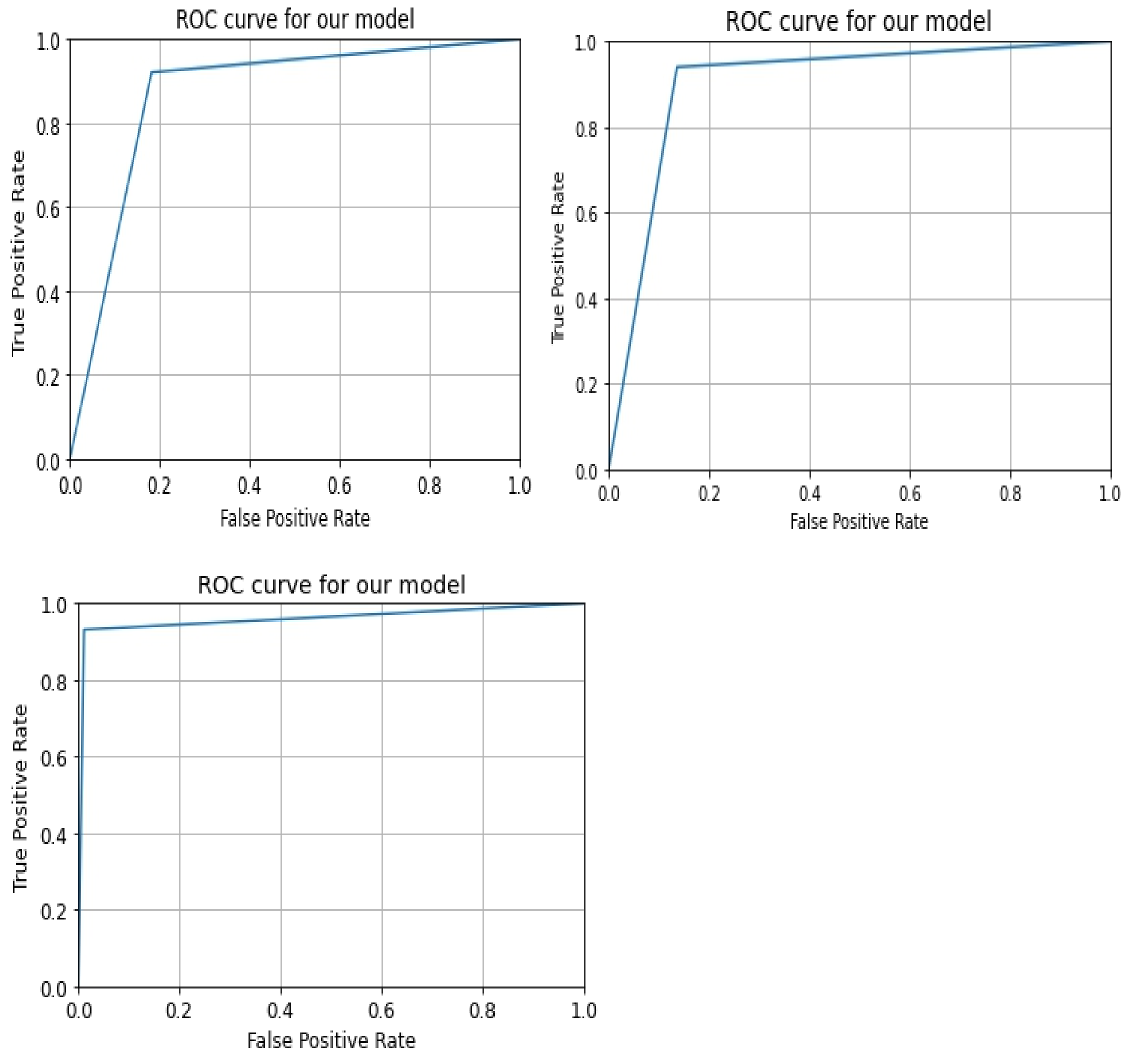


Figure 8: Roc curve for InceptionV3 model a)10 epochs b)100 epochs c)500 epochs

For all three cases area under the curve is greater for InceptionV3 model than VGG19 model.

Confusion matrix is a N*N matrix which is used to evaluate the performance of a model where N is the number of classes to be predicted. It compares actual values with the values predicted by the model. This gives us view of how well our model is performing.

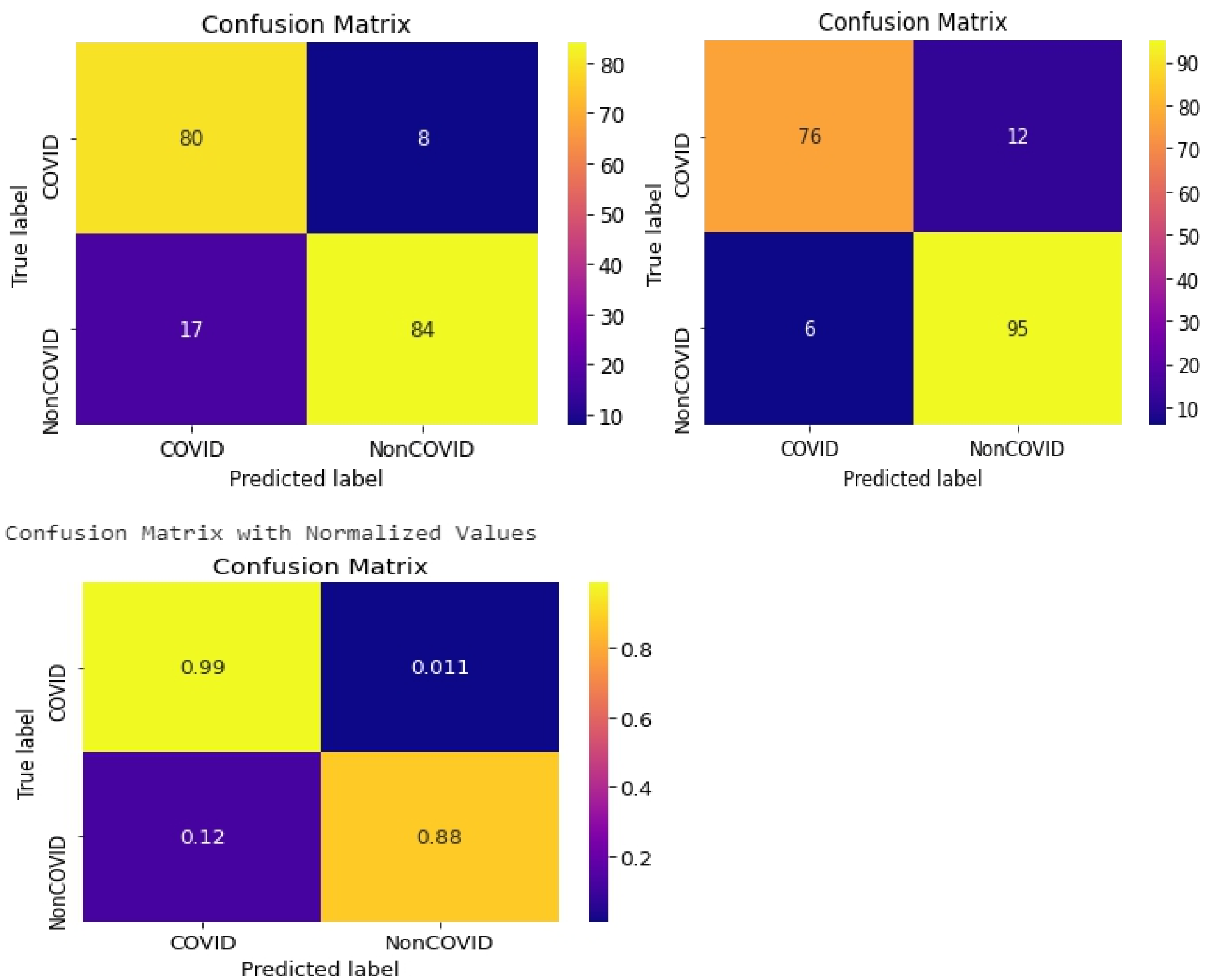
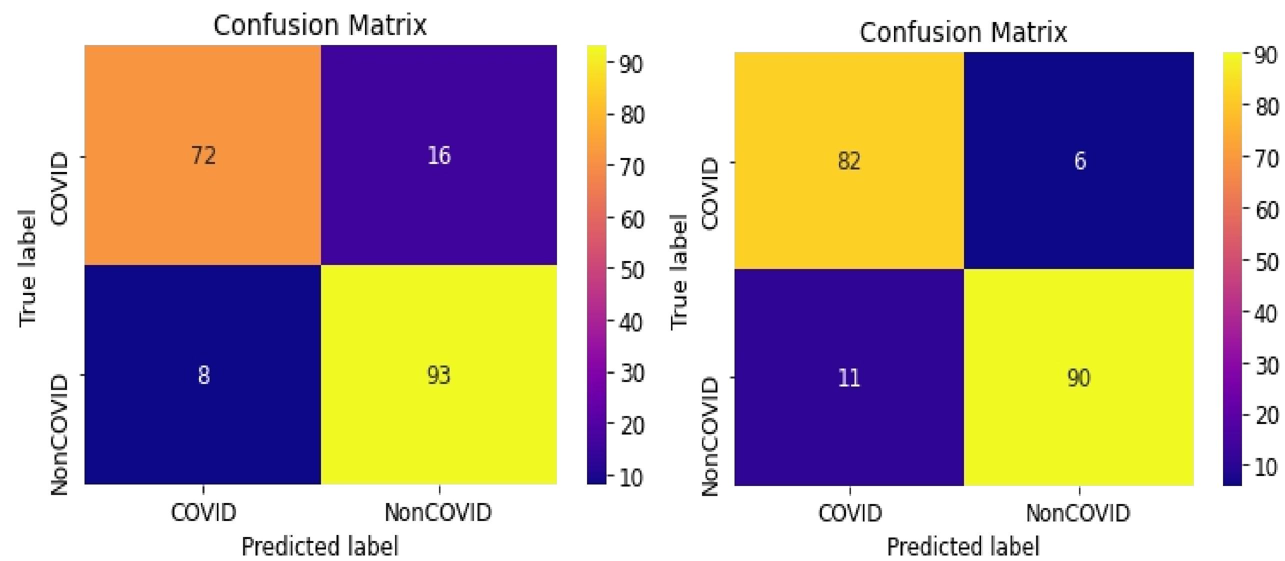


Figure 9: Confusion matrix of VGG19 a)10 epoch b)100 epochs c)500 epochs



Confusion Matrix with Normalized Values

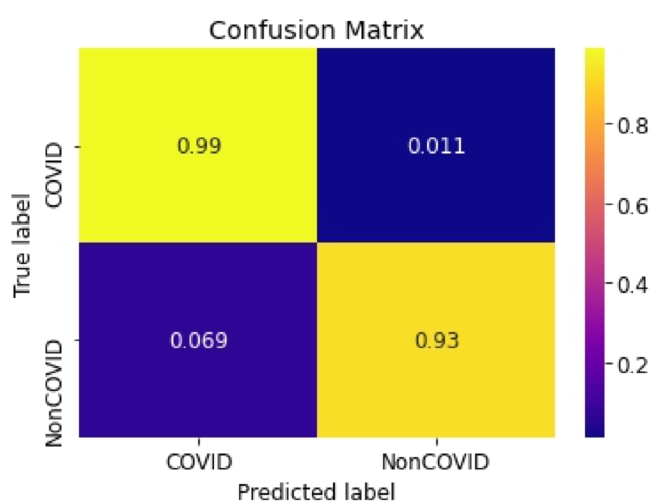
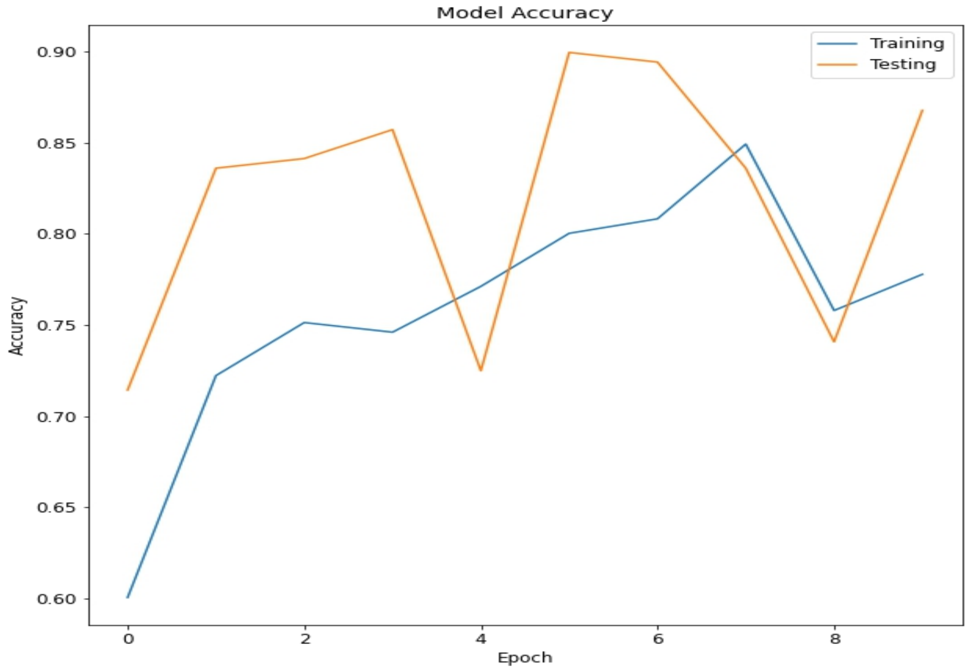


Figure 10: Confusion matrix of InceptionV3 a)10 epoch b)100 epochs c)500 epochs

Loss value implies hoe poorly or well a model behaves after each iteration of optimization. Accuracy is a measure of hoe accurate is the model's accuracy compared to the true data.



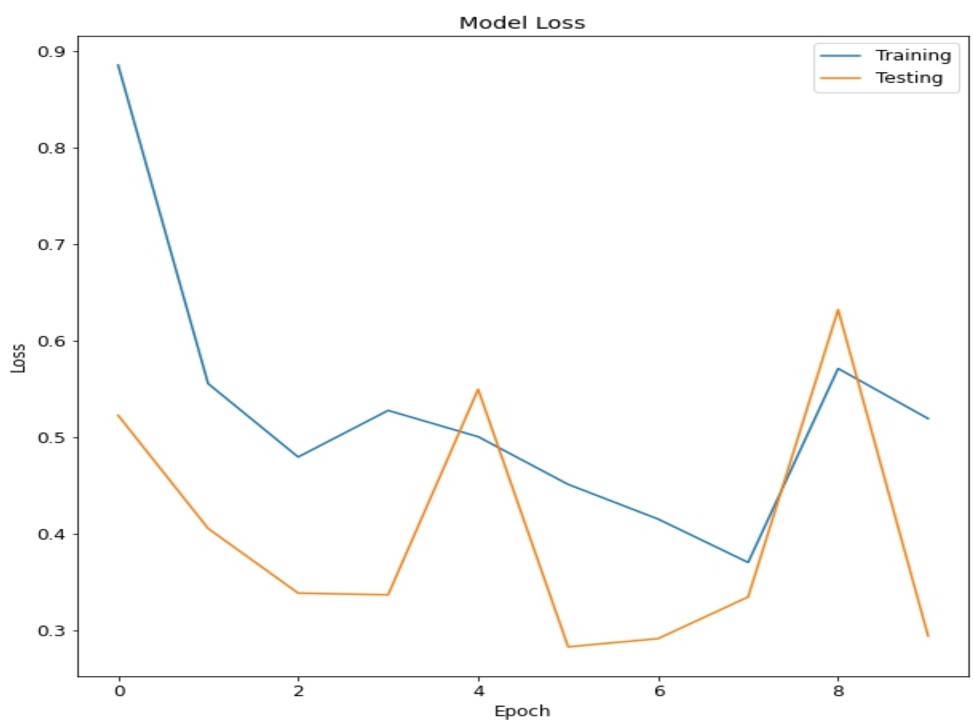


Figure 11: Model Accuracy and Model Loss for VGG19(10 epochs)

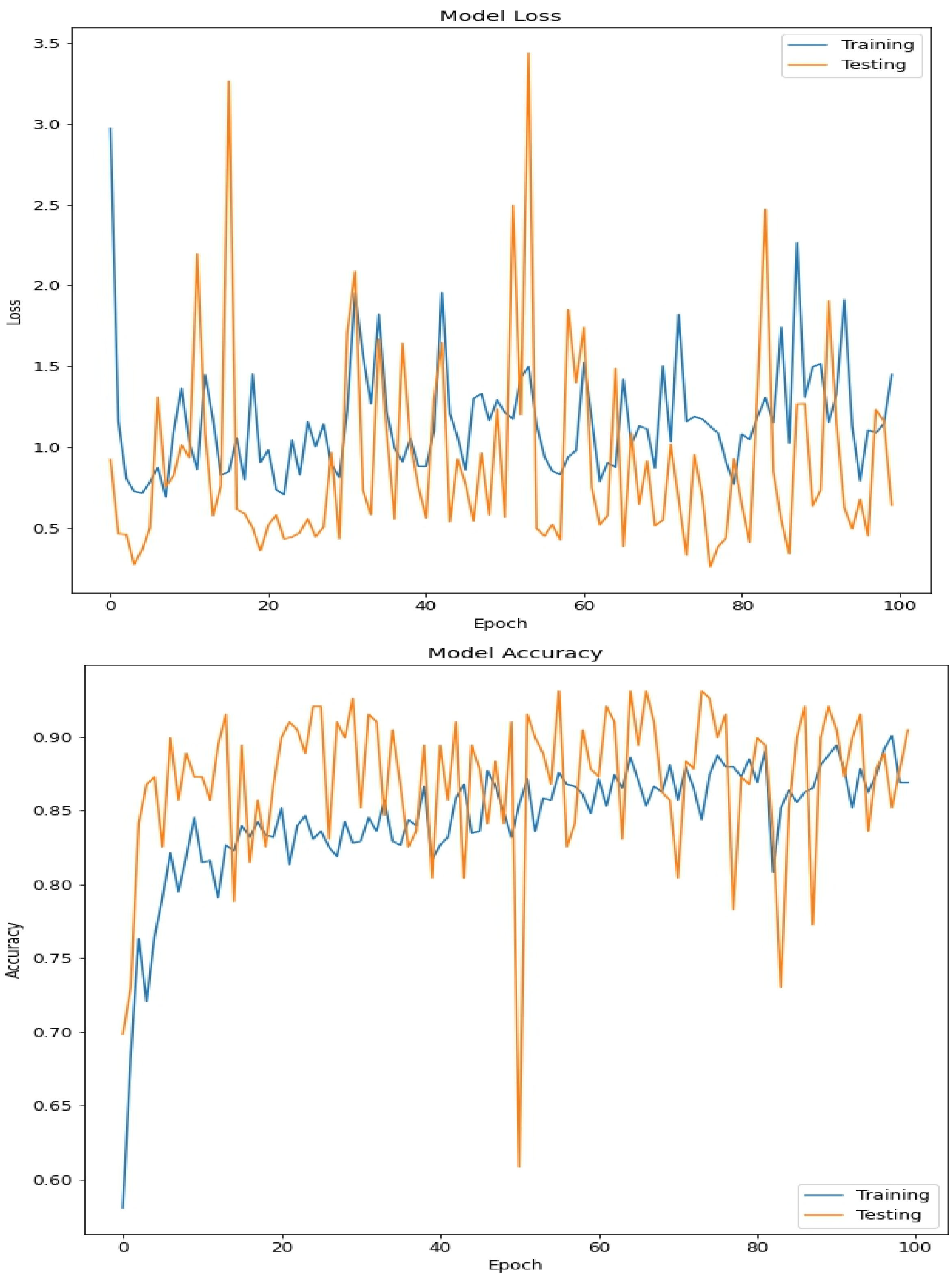
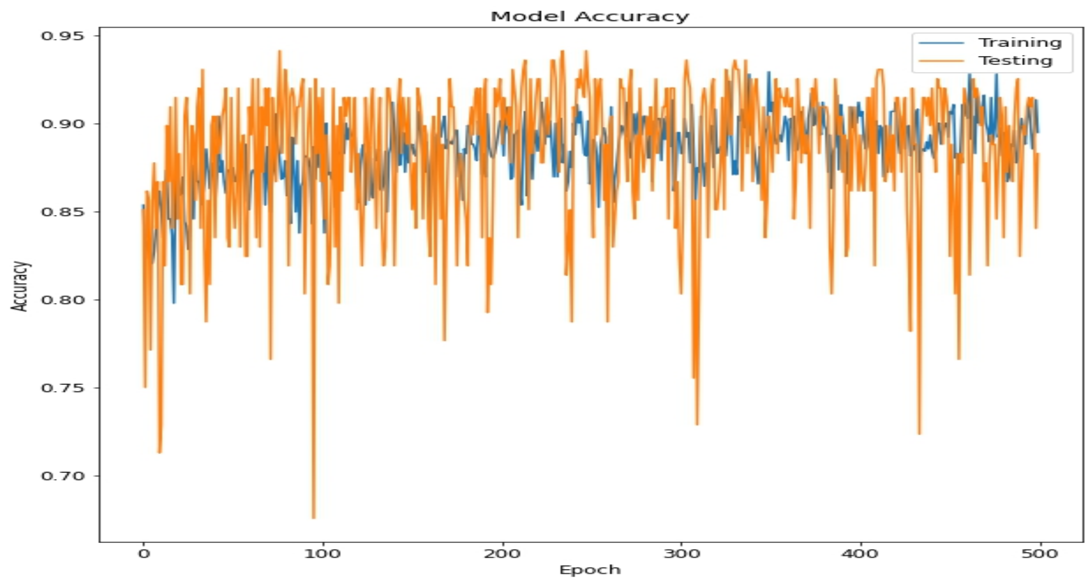


Figure 12: Model Accuracy and Model Loss for VGG19(100epochs)



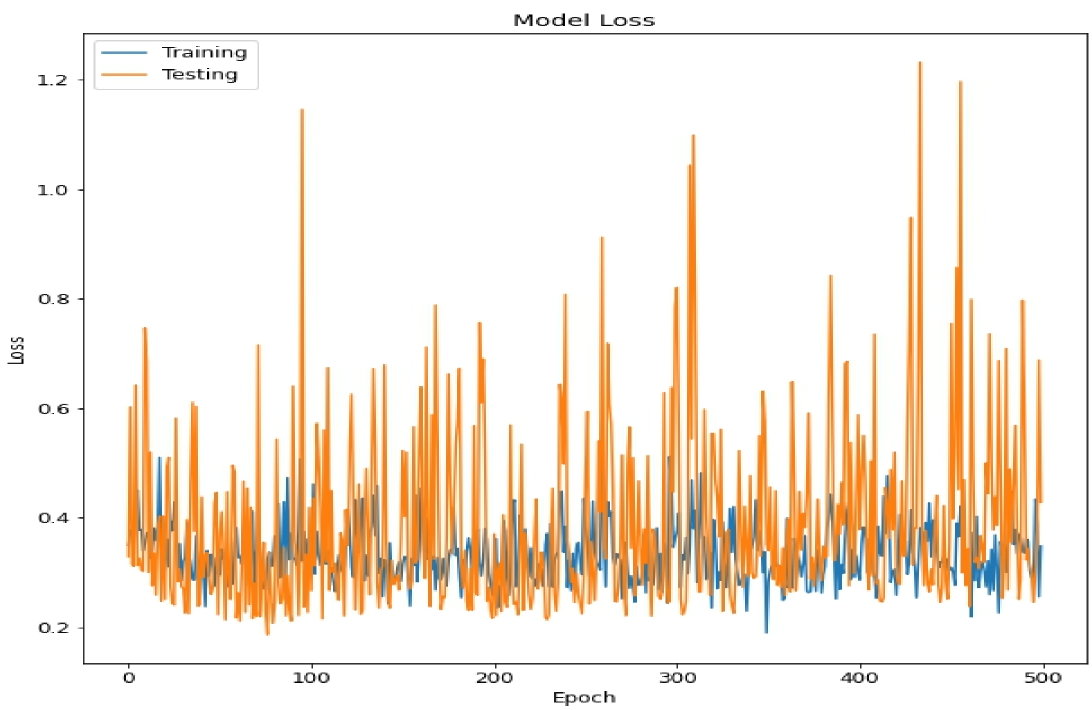


Figure 13: Model Accuracy and Model Loss for VGG19(500epochs)

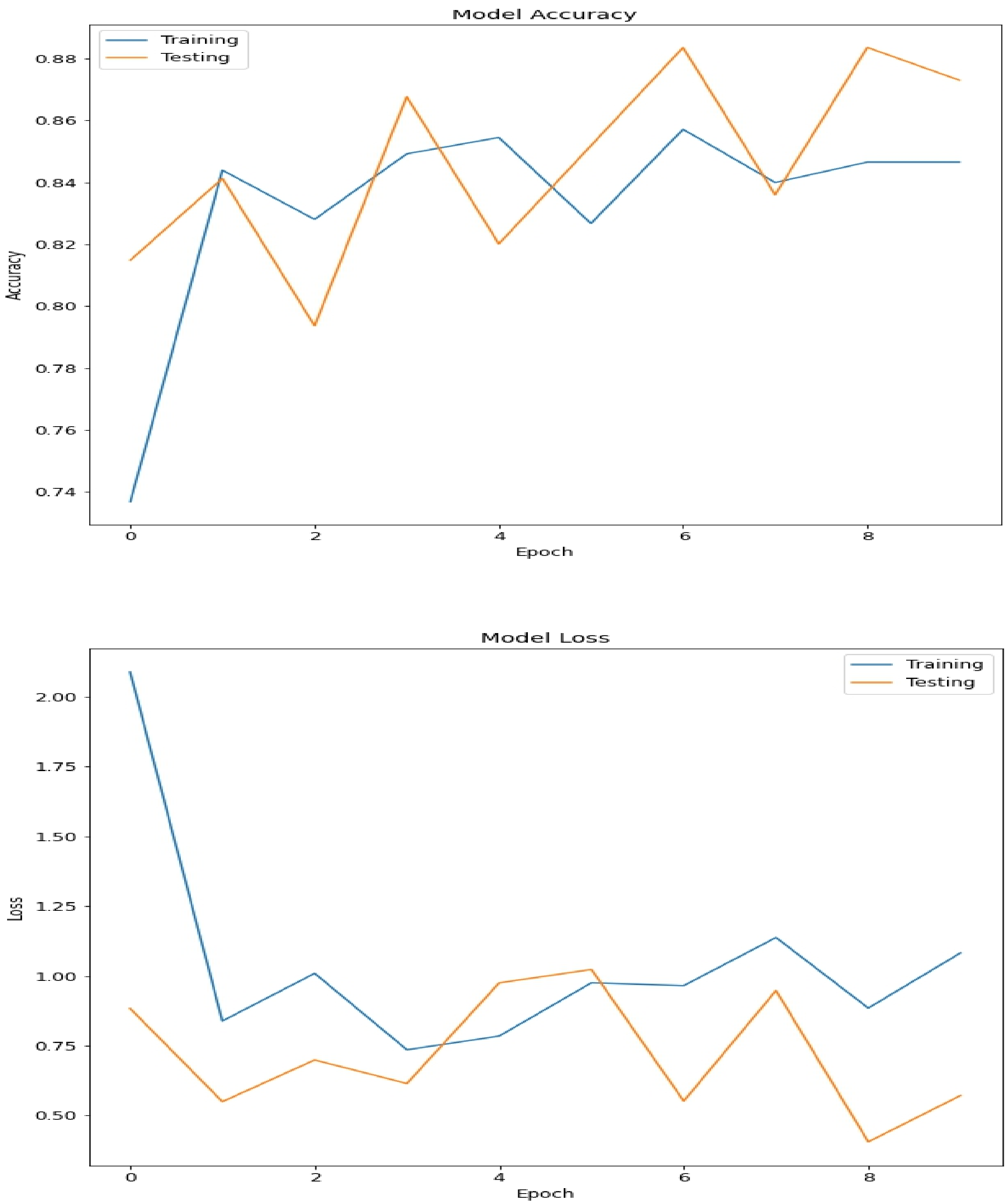


Figure 14: Model Accuracy and Model Loss for InceptionV3(10 epochs)

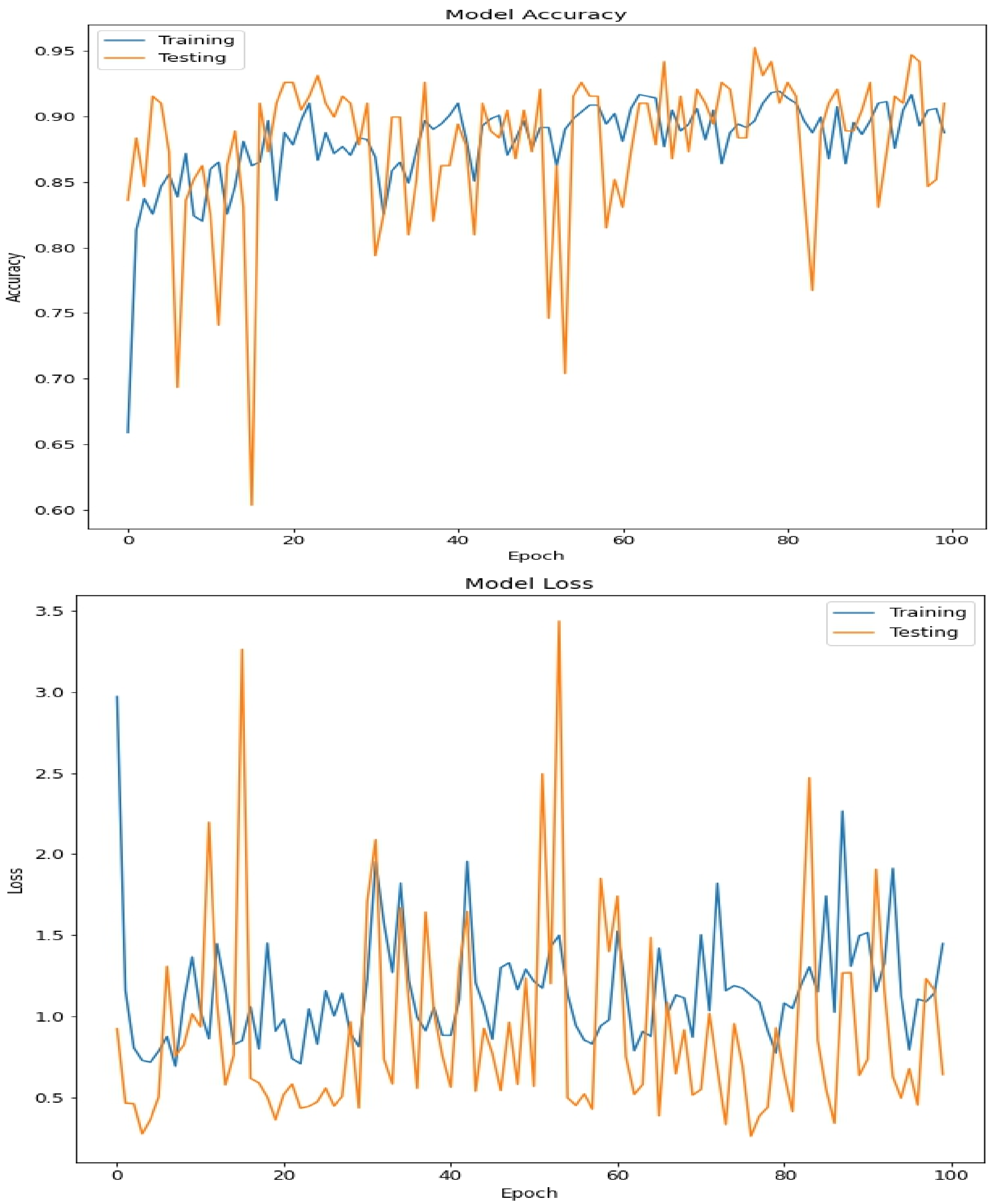
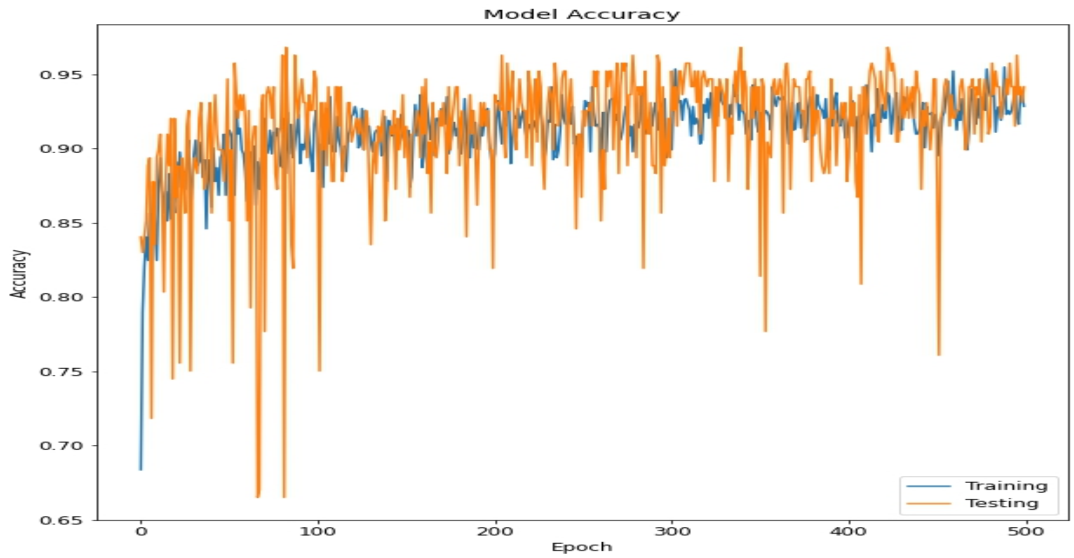


Figure 15: Model Accuracy and Model Loss for InceptionV3(100 epochs)



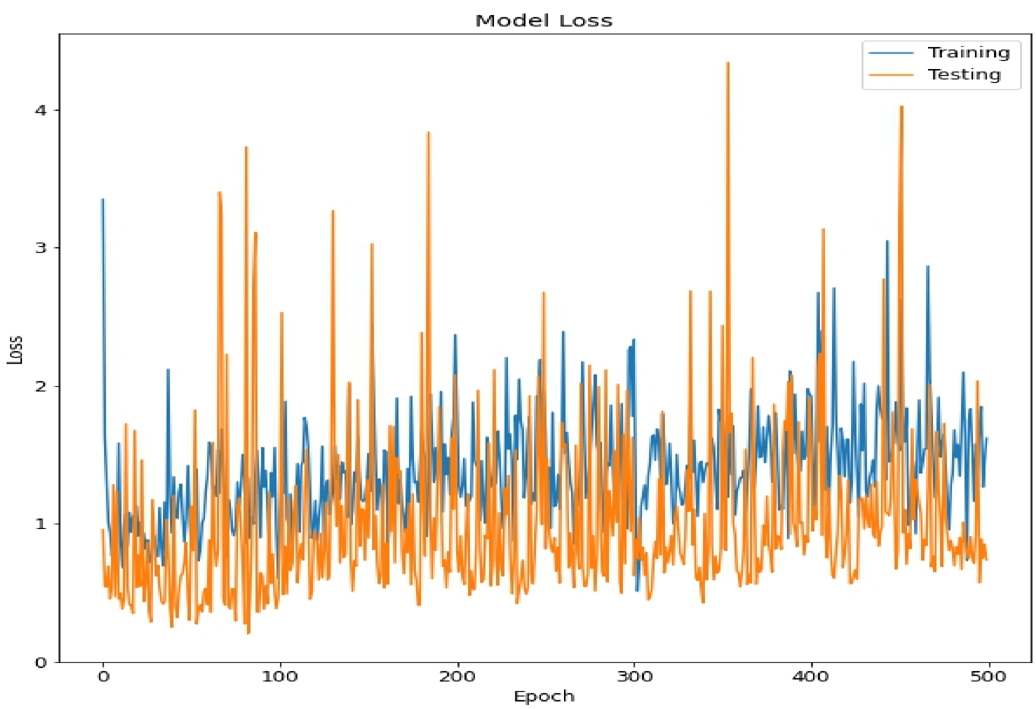


Figure 16: ModelAccuracy and Model Loss for InceptionV3(500 epochs)

4.2 Comparison of VGG19 and Inception V3 model with regards to performance matrices

Table: Comparison of VGG19 and InceptionV3

Model	#epochs		Precision	Recall	F1-Score	Accuracy
VGG19	10	0	0.82	0.91	0.86	0.87
		1	0.91	0.83	0.87	
	100	0	0.93	0.86	0.89	0.91
		1	0.89	0.94	0.91	
	500	0	0.88	0.99	0.93	0.93
		1	0.99	0.88	0.93	
InceptionV3	10	0	0.90	0.82	0.86	0.87
		1	0.85	0.92	0.89	
	100	0	0.88	0.93	0.91	0.91
		1	0.94	0.89	0.91	
	500	0	0.92	0.99	0.96	0.96
		1	0.99	0.93	0.96	

Accuracy of the model in increasing as we increase the no of epochs. VGG19 had accuracy of 0.87 when trained for 10 epochs ,0.91 when trained with 100 epochs and 0.93 when trained with 500 epochs. Inception V3 has accuracy of 0.87 when trained for 10 epochs ,0.91 when trained with 100 epochs and 0.99 when trained with 500 epochs. Overall the accuracy of InceptionV3 model is high and is suitable for training sensitive medical data such as this one. With 500 epochs we get the best result as the model were optimized with each epochs and can be seen in table above. It can also be inferred from roc curve that inception model performs better.

CHAPTER 5

CONCLUSIONS

5.1 Conclusion

We have introduced some underlying outcomes on distinguishing COVID-19 positive cases from chest X-Rays utilizing a profound learning model. We have illustrated critical improvement in execution over COVID-Net, the main openly kept up instrument for characterization of COVID-19 positive X-Rays, on the equivalent chest X-Rays pneumonia dataset. The outcomes look encouraging, however the size of the openly accessible dataset is little. We intend to additionally approve our methodology utilizing bigger COVID-19 X-Rays picture datasets and clinical preliminaries. Overall the accuracy of InceptionV3 model is high and is suitable for training sensitive medical data such as this one. With 500 epochs we get the best result as the model were optimized with each epochs and can be seen in table above. It can also be inferred from roc curve that inception model performs better.

5.2 Future Scope

- Extension of present model
- Improve Data Representation
- Introduce new features such CT Scans
- Introduce new models and parameters
- Deploy the project on web

5.3 Last Few Words

We learned a lot through this project. This project has sharpened our concept of machine learning, deep learning and the software-hardware concepts.

We learned a lot about different documentation. The piece of software we developed is intended to serve the healthcare system of the world. The success of this project may give happiness to millions of healthcare workers around the world. This project not only tested our technical skills but also our temperament.

There were times that we almost lost hope but we recovered through constant concentration and hard work.

If any kind of suggestion, improvements, more efficient development idea please feel free to communicate with us.

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