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DIAGNOSIS OF COVID-19 THROUGH RADIOLOGY IMAGES USING MACHINE LEARNING TECHNIQUES

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Abstract

The period of the world being infected with the corona virus is considered one of the difficult times that cannot be forgotten. The suffering was great in most countries at the beginning of the virus. There were not many tools to confront the virus, which led to many infections and losses. After eliminating the virus and eliminating it thanks to many technologies and developments, it became necessary to study cases of infection and provide a tool for diagnosing those infected. Many datasets were made available to researchers, and it became necessary for us to compare the performance of available systems and develop an accurate and effective model for diagnosing the virus. The importance that we present in our proposed idea is that there is an effective way to identify those infected with the virus. The model's performance can be used to diagnose diseases and other injuries by analyzing ct images. Those infected with the virus are diagnosed with pneumonia and cases are normal. Alexnet, resnet, vgg16, lenet, googlenet and zfnet are effectively used in diagnosis and classification. The data we obtained from al zahra hospital was specifically adapted for use in our proposed system. The total number of labeled samples is 6,396 images, divided into 4,237 pneumonia, 1,583 normal, and 576 infected with covid-19. Ten-fold cross-validation is commonly used to evaluate the accuracy of algorithms. This involves dividing the data set into two subsets: the training set, where the classifier is built, and the testing set, where the classifier is evaluated. The accuracy of the algorithm is estimated by averaging the value of the results obtained from the ten-fold cross-validation procedure. To achieve this, the dataset is evaluated for our results, and thus our proposed system features accurate diagnosis and classification.

Class loading based on image dataset (labels: covid, pneumonia, normal). Implement cnn with transfer learning in two ways:

• load the pre-trained alexnet network, and fine-tune the last three layers for the new classification by training the network on the training data.

• reuse the pre-trained alexnet network to extract features from the "fc7" layer and then classify those features using a support vector machine (svm) model where those features are extracted from the training and testing images.

The classification is evaluated using test examples and examining the difference between images using cnn as classifier and feature extraction.

Month year, …….page (example: november 2017, 129 pages).

Keywords: alexnet, resnet, vgg16, cnn, covid19, image processing, classification.

Introduction

Coronavirus (COVID-19) is a worldwide threat and must be combated with all available scientific approaches. Examining medical images is a well-established method that has the potential to aid in the diagnosis of COVID-19. The challenges people face in their daily lives, especially those that threaten human health, pose a significant risk that must be addressed. A significant amount of scientific research is being conducted on the development of weapons to combat viruses harmful to human health. Systems for identifying and diagnosing infected patients are being developed with the help of contemporary technologies and machine learning image processing technology. ML has demonstrated exceptionally high performance in various image processing applications such as image analysis, image classification, and image segmentation. In order to create the model, photographs of real sick people must be presented in addition to photographs of healthy, uninfected people.

Image classification is typically accomplished by first extracting important features from images to be classified by a descriptor. Classification is a task that can be accomplished with the help of classifiers, such as support for machine vectors and other algorithms. These aspects can be utilized in these efforts. Unlike hand-crafted features, methods based on deep neural networks provide outstanding performance in classifying images based on retrieved features. Based on the properties of ML, many initiatives have used machine learning-based algorithms to categorize chest X-ray images into one of two categories: COVID-19 patient category and normal condition category.

Orthogonal moments and the variables that describe them have recently emerged as useful tools used in various image processing and pattern recognition applications. There are reports of successful applications of feature extraction using image moments for various applications. The aim of this study is to present an accurate classification approach for COVID-19 chest X-ray image based on the extraction of features and their subsequent application in the classification process.

We created a strategy to classify COVID-19 based on chest X-ray. Chest X-ray images are processed by a method that uses machine learning techniques to extract features. After the features are obtained, they are divided into test and training sets. We then initialize the photos within the features by applying our algorithm and then delete information that is meaningless or irrelevant. This technique creates a collection of potential solutions by identifying each solution using a classifier derived from a training set.

This is accomplished by determining the value of “fit” and then selecting the option that provides the best results.

The proposed idea is unique in this field due to the techniques used in creating the system. COVID, pneumonia and healthy x-ray images of the lungs are detected and classified using pre-trained ResNet, VGG16 and AlexNet CNN. Features and network layers are added to build the system and transfer learning. The proposed system is implemented after successive stages. The first stages include preparing the images and data entering the system. To define the categories, the category (tags: Covid, pneumonia, and normal) based on the image dataset is loaded. The validated ratio is often used to split samples to provide training and testing data.

The proposed system is mainly based on the pre-trained AlexNet network model. The settings of the modeling network are changed and the last three layers of the new classification are modified and adjusted by training the network on the training data. Features are extracted and classified according to previously declared classes. Classification performance is evaluated by using test samples and examining the difference between image classification using CNN as a classifier and feature extraction tool.

The proposed idea involves relying on the most significant network to determine the content of the image and classify it accordingly. The system has been prepared to be the most important system that decision makers can subsequently adopt. Many images that bear the characteristics of people infected with pneumonia and the Covid-19 virus can be classified.

I. SOLAR PLANTS MONITORING SYSTEM (10 BOLD)

2. MATERIAL AND METHOD

Machine learning is a field of computer science and artificial intelligence that focuses on algorithms and data to simulate human learning processes in order to increase their precision [19] . The advancement of technology in the areas of storage and processing power in recent years has facilitated the development of new machine learning-based products, including but not limited to driverless vehicles.

The emerging field of data science places significant emphasis on the important role played by machine learning. Through statistical techniques, algorithms are instructed to perform categorization or prediction as well as uncover important revelations in data mining efforts. The insights outlined above serve as a driving force for decision-making processes in both applications and businesses, with the end goal being to positively impact key growth metrics. The expanding and evolving nature of big data will lead to increased market demand for professionals in the field of data science. Individuals will be tasked with helping identify the most relevant business questions and the relevant data needed to address them.

2.1. Simulation (Times New Roman 10pt)

The learning system of the machine learning algorithm can be divided into three main components. Figure (3.1) shows the components of machine learning.

1. The use of machine learning algorithms is often used for prediction or classification purposes within the framework of decision making. The algorithm will create a model prediction from input data that may or may not be categorized.

2. Error function is a mathematical tool used to evaluate the accuracy of a model's predictions. In the presence of identified samples, an error function can be used to evaluate the accuracy of the model.

3. The model optimization process involves adjusting the model's weights to minimize the discrepancy between the model prediction and known examples in the training set, thus improving the fit of the model to the data points. The iterative process of “evaluation and optimization” is carried out by the algorithm, which will autonomously adjust the weights until a predetermined level of accuracy is achieved.

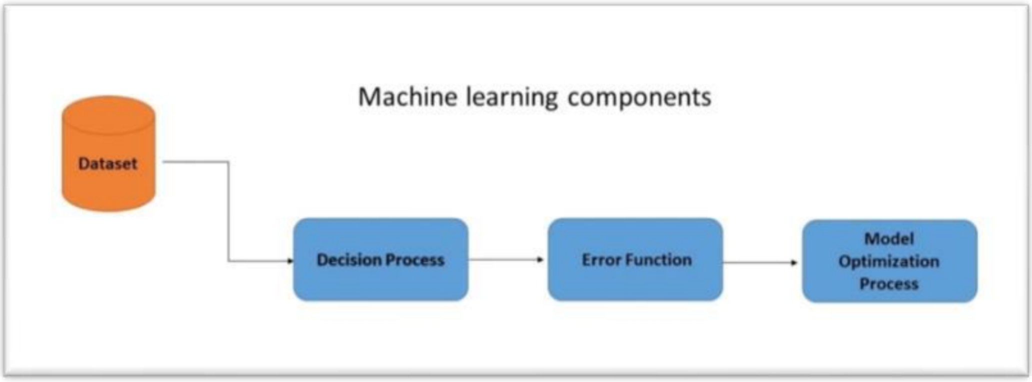


Figure 2.1. Machine Learning Components

2.1.2 Machine Learning Categories

Three main categories can be used to classify machine learning models [21]. Like Figure

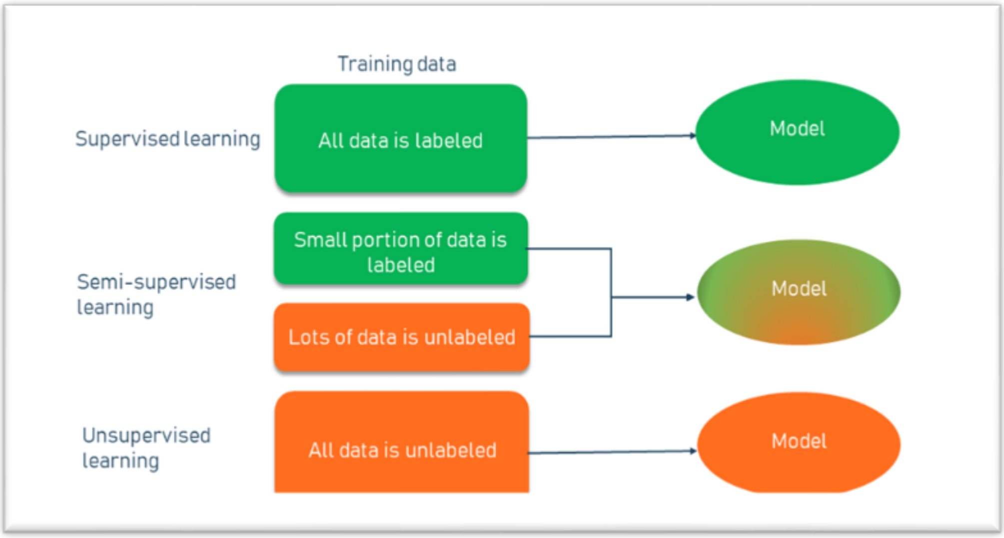


Figure 2.2. Categories of Machine Learning Methods

1. Supervised machine learning

Supervised learning, which is also used to predict outcomes, refers to using the process of teaching computers to accurately classify data.

The model feeds it input data until it fits well. This occurs as part of a cross-validation procedure to ensure that the model fits well or poorly. A common example is categorizing spam in a separate folder from your email and How to Help Moderated Learning Support Companies. Neural networks. Bayes, random forests, and logistic regression. Support vector machines (SVM) are some of the techniques used in supervised learning
learning.

2. Unsupervised machine learning

Unsupervised learning analyzes and assembles new data sets using machine learning algorithms. It identifies hidden algorithms or data sets without human assistance. Since this strategy can find similarities in information, analyze new data, interoperate tactics, identify images and patterns and segment beneficiaries. In addition, dimensionality reduction is used to reduce the amount of attributes in the model. Two common methods for this are (SVD) and principal components analysis (PCA). Neural networks, k-means clustering techniques, probabilistic clustering techniques, and singular value analysis are other algorithms used in unsupervised learning. Figure (3.3) is a visual example of an unsupervised dimension reduction technique

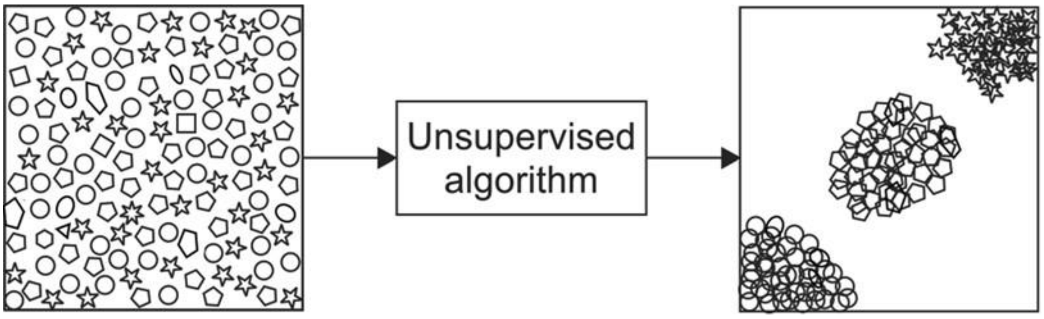


Figure 2.3. A visual example of the unsupervised size reduction technique

3. Semi-supervised learning

A satisfactory compromise between machine and non-machine learning is provided by semi-mechanical learning. It extracts features and guides classification from a larger unlabeled dataset when training with a sparse dataset.

The lack of sufficiently processed data for an action-supervised learning system can be addressed through semi-supervised learning. It is also good to have data tags

3.1.3 Medical applications in machine learning

Due to advances in computing power, storage capacity and memory capabilities, and the exponential growth of data generation, computers have become effective at performing a wide range of complex tasks with remarkable precision. Machine learning (ML) refers to the academic field and technological framework that enables computers to execute complex tasks. As an academic field, machine learning encompasses various components derived from mathematics, statistics, and computer science. Machine learning plays a crucial role in facilitating advancements in artificial intelligence. The use of this technology is being used effectively in both academic and industrial settings to facilitate the advancement of “smart products” capable of producing precise predictions by leveraging a wide variety of data sources [22]. So far, the primary recipients of the proliferation of big data, machine learning, and data science in the 21st century have been predominantly industries that can accumulate such data and employ the necessary personnel to revolutionize their offerings.

Learning methodologies developed in these sectors have significant potential for advancing medical research and clinical care, especially in light of the increasing use of electronic health records (EHRs) by healthcare providers. The primary recipients of the proliferation of big data, machine learning, and data science in the 21st century have been predominantly industries with the capacity to accumulate such data and employ the necessary personnel to revolutionize what they deliver. Learning methodologies developed in these sectors have significant potential for advancing medical research and clinical care, especially in light of the increasing use of electronic health records (EHRs) by healthcare providers. The primary recipients of the proliferation of big data, machine learning, and data science in the 21st century have been predominantly industries with the capacity to accumulate such data and employ the necessary personnel to revolutionize what they deliver.

Learning methodologies developed in these sectors have significant potential for advancing medical research and clinical care, especially in light of the increasing use of electronic health records (EHRs) by healthcare providers. There are two specific areas in the medical field that can gain an advantage through the use of machine learning methodologies: diagnosis and outcome prediction. This includes the capacity to recognize high-risk medical emergencies, such as relapse or progression to an alternative state. In recent studies, machine learning algorithms have demonstrated their effectiveness in accurately classifying skin cancer through analysis of images, achieving accuracy comparable to that of a trained dermatologist [23] . Additionally, these algorithms have been used to predict progression from pre-diabetes to type 2 diabetes using routinely collected electronic health record data [24].

The use of machine learning in conjunction with natural language processing (NLP) is expected to experience an increasing trend as it enables understanding and interpretation of unstructured textual data. Researchers have successfully gained new insights by integrating machine learning and natural language processing (NLP) methodologies. This information was obtained from a variety of sources, including clinical incident reports, social media activity, clinician performance reviews [25], and patient reports following cancer treatment. Using unstructured data to gain insight into quality, safety, performance and early diagnosis can be highly advantageous. In a recent study,

Machine learning is expected to have a significant impact on the advancement of educational healthcare systems. Educational health systems can be defined as environments that integrate science, informatics, incentives, and culture to promote continuous improvement and innovation. In practical application, these systems have the potential to operate at various levels, from small-scale group applications to large-scale national service providers. It is designed to integrate various data sources and use complex machine learning algorithms. The result will consist of a seamless flow of data-driven insights aimed at advancing biomedical and public health research as well as improving the quality of healthcare [27].

3.2. Deep Learning

Deep learning constitutes a subfield of machine learning, characterized by the use of neural networks consisting of three or more layers [28]. Neural networks attempt to replicate the actions of the human brain, allowing it to extract information from vast amounts of data, although they fall short of imitating its proficiency. Although a neural network containing a single layer can produce predictions that are quite close to the true values, the inclusion of complementary hidden layers can enhance the optimization process and improve the precision of the predictions.

The use of deep learning techniques is the key driver behind a multitude of artificial intelligence (AI) applications and services that have the capacity to enhance automation by executing analytical and physical tasks without the need for human intervention. Deep learning technology underpins ordinary products and services, including but not limited to digital assistants, voice-activated television remote controls, and credit card fraud detection. It is also a key component of emerging technologies such as autonomous vehicles. Deep learning neural networks, also known as artificial neural networks, attempt to replicate the functionality of the human brain using a mixture of data inputs, weights, and biases. These elements work together to accurately recognize, classify, and identify objects in the data.

Deep neural networks consist of multiple layers of interconnected nodes [29]; each layer gradually improves and optimizes the prediction or categorization based on the previous layer. The process of transmitting data sequentially over the network is called forward propagation. The visible layers of the deep neural network are called input and output layers. The input layer of the deep learning model is responsible for receiving and processing the input data, while the output layer is responsible for creating the final prediction or classification.

Backpropagation is an algorithmic process that uses techniques such as gradient descent to calculate prediction errors and then vary the weights and biases of the function. This is accomplished by going back through the layers of the model to train the model. Forward propagation and backpropagation together enable a neural network to generate predictions and correct any errors accordingly. As time goes by, the algorithm becomes increasingly accurate.

It explains the basic type of deep neural network in the easiest concepts. Deep learning algorithms are characterized by their high level of complexity [30] and encompass a variety of neural network architectures tailored to address specific datasets or problems. For example:

• Convolutional neural networks (CNNs) are mainly used in the fields of computer vision and image classification [31]. They have the ability to identify features and patterns found in an image, thus facilitating tasks such as object detection or recognition. In 2015, a CNN beat a human for the first time in the object recognition challenge.

• Recurrent neural networks (RNNs) are widely used in the fields of natural language processing and speech recognition due to their ability to effectively model sequential or time-series data [32].

3.3. CONVOLUTIONARY NEURAL NETWORK

3.3.1 CNN Types

First, LeNet is a groundbreaking convolutional neural network (CNN) specifically developed for the purpose of accurately identifying and classifying handwritten characters. This proposal was put forward by Yann LeCun, Leon Bottou, Yoshua Bengio and Patrick Haffner in the late 1990s. The LeNet architecture consists of a fully connected layer and a softmax classifier, as well as a series of convolution and pooling layers. This particular application of deep learning for computer vision was one of the first examples to achieve success. Grayscale input images are used by financial institutions to identify numerical values written on checks. Figure (3.4) shows the LetNet algorithm architecture.

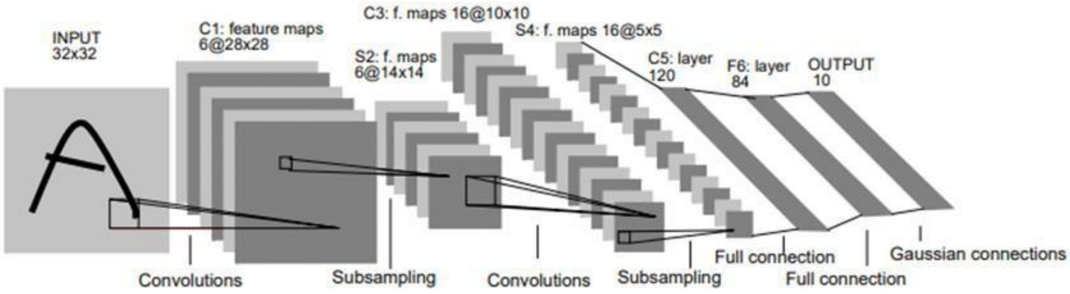


Figure 3.4. LetNet algoritma mimarisi [34]

The other convolutional neural network is the Visual Geometry Group (VGG), a research group based in the Department of Engineering Sciences at the University of Oxford. The VGG research team has gained significant recognition for its contributions in the field of computer vision [35], particularly in the field of convolutional neural networks (CNNs). The VGG group has made significant contributions in this field; One of his best-known achievements is the development of the VGG model, often referred to as VGGNet. The VGG model is a deep neural network that achieved outstanding performance in the ImageNet Large-Scale Visual Recognition Challenge in 2014 and has since been widely used as a standard for evaluating image classification and object detection tasks [36].

The VGG model stands out for its use of compact convolutional filters (3x3) and a deep architectural design (up to 19 layers) that makes it easy to extract increasingly complex features from input images. The VGG model includes maximum pooling layers to effectively reduce the spatial resolution of feature maps and improve the receptive field. This architectural choice increases the model's capacity to accurately identify objects of different scales and orientations. The VGG model has served as an important source of inspiration for subsequent research efforts in the field of deep learning [37]. This effect has been observed in the progression of neural networks with increasing depth, as well as in the integration of residual connections to improve gradient flow and improve the stability of training processes,

ResNet is a widely used model like other types. ResNet, also known as Neural Network, is a collection of deep convolutional neural networks specifically developed to solve the problem of vanishing gradients [38], which frequently occurs in networks with multiple layers.

The underlying concept of ResNet involves the use of “residual blocks” to facilitate the direct flow of gradients through the network, making it easier to train networks at significant depth.

The residual block consists of multiple convolutional layers, usually two or more, which are then followed by an activation function. Additionally, a shortcut link is included within the residual block, allowing the original input to bypass the convolutional layers. This shortcut connection then adds the original input directly to the output of the convolutional layers following the activation function.

This allows the neural network to obtain residual functions that represent the disparity between the input and output of the convolution layers, rather than trying to learn the exact mapping directly. The use of residual blocks makes it easier to train extremely deep networks [39] spanning multiple layers, thus effectively reducing the problem of vanishing gradients.

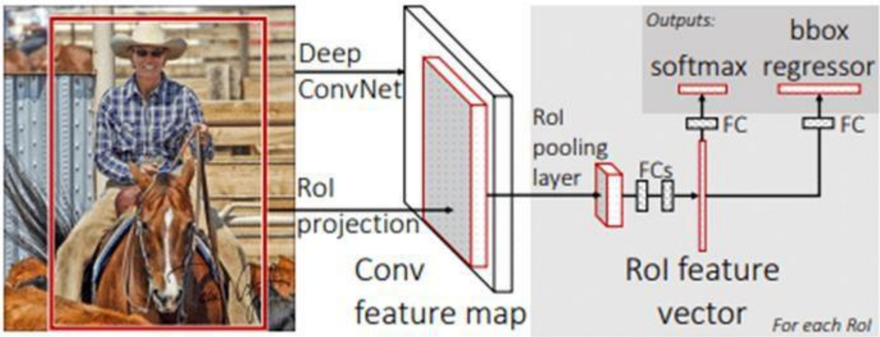
Region-Based Convolutional Neural Network (R-CNN) was first proposed as a two-stage methodology for the object detection task in 2013 [40]. Initially, the input image is divided into regions of interest (ROIs) using selective search. This algorithm, which has high computational intensity, produces region suggestions by taking into account various image features such as texture and color. Each region of interest (ROI) is then processed by a convolutional neural network (CNN), resulting in a feature vector of predetermined length. The Convolutional Neural Network (CNN) used in the region-based Convolutional Neural Network (R-CNN) framework typically consists of a pre-existing network such as AlexNet or VGG that has been pre-trained [41].

Feature vectors are used to classify the object within the region of interest (ROI) and make predictions about bounding box coordinates. Although R-CNN showed a remarkable performance in its time, the training and testing processes were quite time-consuming. This can be attributed to the need to consider multiple region proposals for each image. R-CNN, together with Fast R-CNN and Faster R-CNN, constitute a collection of object detection models designed by researchers from UC Berkeley and Microsoft Research [42]. These models represent a significant advance over previous approaches in the field of object detection.

Fast R-CNN The Fast R-CNN method, first introduced in 2015, increased the performance of the R-CNN approach by eliminating the need for a separate feature extraction process for each region recommendation [43]. In contrast, the convolutional neural network (CNN) processes the entire image, resulting in a feature map that is universally used by all proposed regions.

Region of Interest (ROI) pooling is then used to aggregate each ROI into a feature map with a predetermined size. This feature map is then fed into a series of fully connected (FC) layers to generate bounding box coordinates and final predictions for object classification.

While the above-mentioned methodology exhibits superior speed and precision compared to R-CNN, it also requires comprehensive training of the entire model.



Şekil 3.5. Hızlı R-CNN algoritması [44]

3.3.2 Importance of CNN

Deep learning is a type of machine learning that requires the use of a neural network consisting of at least three layers. It has been observed that multilayer networks exhibit higher levels of accuracy than single-layer networks. Deep learning applications often use convolutional neural networks (CNNs) or recurrent neural networks (RNNs).

Convolutional Neural Network (CNN) architecture is particularly advantageous in image recognition, image classification, and other computer vision tasks due to its ability to efficiently process large amounts of data and produce predictions with a high degree of accuracy [45]. Convolutional Neural Networks (CNNs) are capable of extracting the features of an object through a large number of iterations, thus eliminating the need for manual feature engineering efforts such as feature extraction.

It is possible to undertake retraining of a Convolutional Neural Network (CNN) for the purpose of a new recognition task [46] or, alternatively, to create a new model by leveraging an existing network equipped with pre-trained weights. The phenomenon mentioned is generally considered transfer learning. This makes it easier for Convolutional Neural Networks (CNNs) to be used by machine learning model developers in a variety of applications and eliminates the need to start development from scratch.

3.4. Dataset and tools used

3.4.1 Dataset

The data used in our proposed idea was obtained from Fatima Al-Zahraa Hospital in Rusafa, Baghdad, Iraq. The dataset includes CT images of people previously infected with Covid-19, including men, women and children. Images are prepared and collected to be used in the idea we propose. The 10-fold cross-validation technique is commonly used to evaluate the accuracy of algorithms. This involves splitting a dataset into two subsets: the training set, from which the classifier is built, and the test set, from which the classifier is evaluated. The accuracy of the algorithm is estimated by calculating the average value of the results obtained by performing the cross-validation process 10 times. To achieve this, the data set is randomly divided into 10 parts; 9 pieces are used for training and 1 piece is used for testing. This entire process is then repeated 10 times using different test data each time. Using this method, we can comprehensively understand the accuracy of the algorithm by considering multiple iterations and variations in the test data.

3.4.2 AlexNet convolutional neural network

AlexNet is an 8-layer deep convolutional neural network shown in Figure (3.6) [49]. AlexNet is available as a pre-trained version of the network trained on over one million images from the ImageNet database using MATLAB (MathWorks, Natick, MA, United States). AlexNet network can classify up to 1000 categories. The image input size of the network is 227 x 227. In the first layer of AlexNet, the convolution window shape is 11x11. The convolution window shape in the second layer is reduced to 5x5, then to 3x3. After the first, second and fifth convolution layers, the network adds maximum pooling layers with window shape 3x3 and number of steps 2 (Table 3.2). After the last convolutional layer, there are two large fully connected layers with 4096 outputs. These layers require approximately 1GB of model parameters

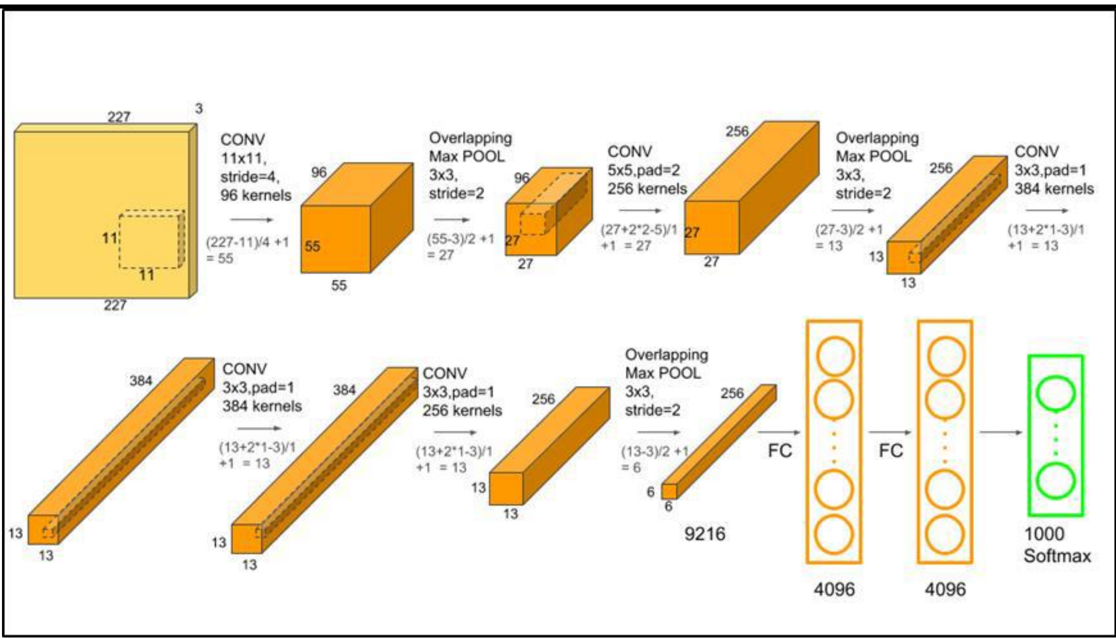


Figure 3.6. Main architecture of AlexNet network

3.4.3 ResNet50 network

AlexNet came first in the LSVRC2012 classification competition held in 2012, achieving an important milestone in the field of computer vision and deep learning. Following this breakthrough, ResNet became another remarkable development in the same field. Originally developed for image recognition tasks, ResNets have the potential to be applied to a variety of non-computational tasks, resulting in improved accuracy, as noted in the paper. Resnet50 consists of several elements, starting with a 7x7 kernel and a convolutional layer using 64 different kernels, all with a step size of 2. This contributes to the formation of a single layer in the network. A max pooling layer with a step size of 2 is then added. The next convolutional layers consist of an array of 1x1 kernels (64), then 3x3 kernels (64), and finally 1x1 kernels (256). This layer sequence is repeated three times, resulting in a total of nine layers. Moving forward, a kernel of size 1x1 (128), followed by another kernel of size 3x3 (128), and finally a kernel of size 1x1 (512). This combination is repeated four times, adding an additional 12 layers to the network. Following this, a kernel of size 1x1 (256) is added, then two kernels of size 3x3 (256), and finally a kernel of size 1x1 (1024). This particular configuration is repeated six times, resulting in a total of 18 layers. Moving on, we have a kernel of size 1x1 (512), followed by two more kernels of size 3x3 (512), and finally we have a kernel of size 1x1 (2048). This sequence is repeated three times, adding nine more layers. After these layers comes an average pooling process. The network terminates with a fully connected layer covering 1000 nodes and is terminated with the softmax activation function, thus creating a final layer. In summary, the resnet50 architecture includes a comprehensive arrangement of convolutional layers, max-pooling, kernel sizes, and iterations, resulting in 50 layers in total. This complex network design aims to achieve accurate and efficient image recognition capabilities.

3.4.3 VGG16 network

VGG16, as the name suggests, is a deep neural network consisting of 16 layers. This network is quite large, containing a staggering 138 million parameters, which is enormous even by today's standards. But what sets the VGGNet16 architecture apart from others is its simplicity, which makes it extremely attractive. There is the use of small convolution filters in a VGG network. In VGG16 we can find 13 convolutional layers and three fully connected layers. Let's look at a brief overview of the VGG architecture: First of all, the input of VGGNet is a 224×224 image. During the ImageNet competition, the model's creators standardized the image input size by cropping a 224×224 section from the center of each image. They use the smallest possible receptive field size of 3x3 for convolutional layers in VGG. Additionally, VGG also uses a 1x1 convolution filter as a linear transformation for the input. Following this, we encounter the Rectified Linear Unit Activation Function (ReLU), an important innovation introduced by AlexNet to speed up the training process. ReLU acts as a linear function, producing an output equal to the input for positive values, while producing zero for negative values. To preserve spatial resolution after convolution, VGG applies a convolution step of 1 pixel (the step value indicates the number of pixels the filter "moves" to cover the image). Unlike AlexNet, which uses Local Response Normalization in its hidden layers, VGG uses ReLU in its hidden layers. The decision to avoid Local Response Normalization is due to the fact that it increases both training time and memory usage without significantly increasing overall accuracy. Pooling layers come into play after multiple convolution layers, serving to reduce the dimensionality and number of parameters in the feature maps created during each convolution step. This is especially important considering that the number of available filters increases from 64 to 128, to 256, and finally to 512 in the last layers. Finally, VGGNet contains three fully connected layers. The first two layers consist of 4096 channels each, while the third layer consists of 1000 channels, representing one channel for each class

3.4.3 LetNet

Designed by Yann LeCun and colleagues in 1998, LeNet-5 constitutes a seminal convolutional neural network (CNN) architecture known specifically for its effectiveness in handwritten digit recognition. The LeNet-5 architecture implemented in MATLAB starts with an input layer representing a 28x28 grayscale image [54]. Next, a convolution layer with 20 filters of size 5x5 applies the convolution operations, followed by a Rectified Linear Unit (ReLU) activation layer that handles nonlinearity. Maximum pooling, a subsampling technique, reduces spatial dimensions with a pool size of 2x2 and a step of 2. This is followed by another convolution layer with 50 filters and then ReLU activation. Additional maximum pooling further reduces spatial dimensions. The architecture then integrates a fully connected layer with 500 neurons and ReLU activation, followed by another fully connected layer with 10 neurons for digit classification. The softmax activation layer transforms the raw outputs into probabilities and the classification layer specifies the task as classification. The training uses stochastic gradient descent ('sgdm') with specific options, embodying the distinctive design principles that made LeNet-5 fundamental in the evolution of CNNs and deep learning [55].

3.4.4 GoogleNet

GoogleNet, also known as Inception v1, represents an important convolutional neural network (CNN) architecture developed by Google researchers. Introduced in the "Going Deeper with Convolutions" article, this model emerged victorious in the 2014 ImageNet Large Scale Visual Recognition Competition (ILSVRC). GoogleNet addresses the challenges associated with training very deep neural networks and emphasizes computational efficiency [56]. At the heart of its design is the Inception module, a new building block that uses multiple filter sizes (1x1, 3x3, 5x5) and pooling operations in parallel to capture features at different scales. In particular, the architecture includes 1x1 convolutions for dimensionality reduction, global mean pooling instead of fully connected layers for parameter reduction, and auxiliary classifiers in intermediate layers during training to eliminate the vanishing gradient problem. Including batch normalization further increases stability and speeds up training. The overall architecture of GoogleNet consists of stacked Inception modules resulting in global mean pooling, dropout for regularization, and softmax layer for classification. Although GoogleNet is not that common in contemporary use, its innovations significantly influenced later CNN architectures and made a crucial contribution to the development of deep learning models.

3.4.5 ZfNet

ZFNet or Zeiler & Fergus Net is a convolutional neural network (CNN) architecture that emerged as a major milestone in computer vision by securing victory in the 2013 ImageNet Large-Scale Visual Recognition Competition (ILSVRC). Developed by Matthew D. Zeiler and Rob Fergus, ZFNet builds on the foundation laid by AlexNet but introduces notable changes to improve its performance. A distinctive aspect of ZFNet is its increased depth, containing eight layers compared to AlexNet's original five layers. In addition, ZFNet uses smaller filter sizes by combining the 7x7 filter in the first layer with the next 3x3 filters; this strategy is thought to capture finer details in input images [57]. Also noteworthy is the introduction of visualization techniques, such as using deconvolution networks to create visualizations of learned features and providing insight into the hierarchical representations obtained by different layers. ZFNet includes normalization layers, including local response normalization (LRN), to improve generalization and uses max-pooling layers for downsampling and spatial abstraction. Although ZFNet is not as widespread in contemporary use, its success at ILSVRC and its contributions to the understanding of deep learning architectures, particularly in the field of image recognition, have left a lasting impact on subsequent developments in the field**.**

3. RESULTS

3.1. Recommended system specifications

The search for effective strategies to overcome the challenges posed by Coronavirus (COVID-19) has garnered significant scientific attention. Researchers and decision-makers are responsible for efforts to combat the virus, namely data management and identification of infected individuals and

It encountered a significant obstacle such as establishing robust systems with high sensitivity in classification. This issue puts pressure on the resources available to researchers and necessitates the development of strategies for the efficient management and use of data.

The concept of our proposed model is applied to create a multi-stage model as shown in Figure3.1. This illustration demonstrates the potential of AI to contribute to the advancement and improvement of global health systems. Originally developed for classifying generic images, the use of computer vision techniques has been expanded to include medical images such as computed tomography (CT) thanks to the exponential advancement of artificial intelligence. Convolutional neural network (CNN) is a widely used neural network architecture that exhibits significant potential in effectively capturing feature representations compared to other existing approaches.

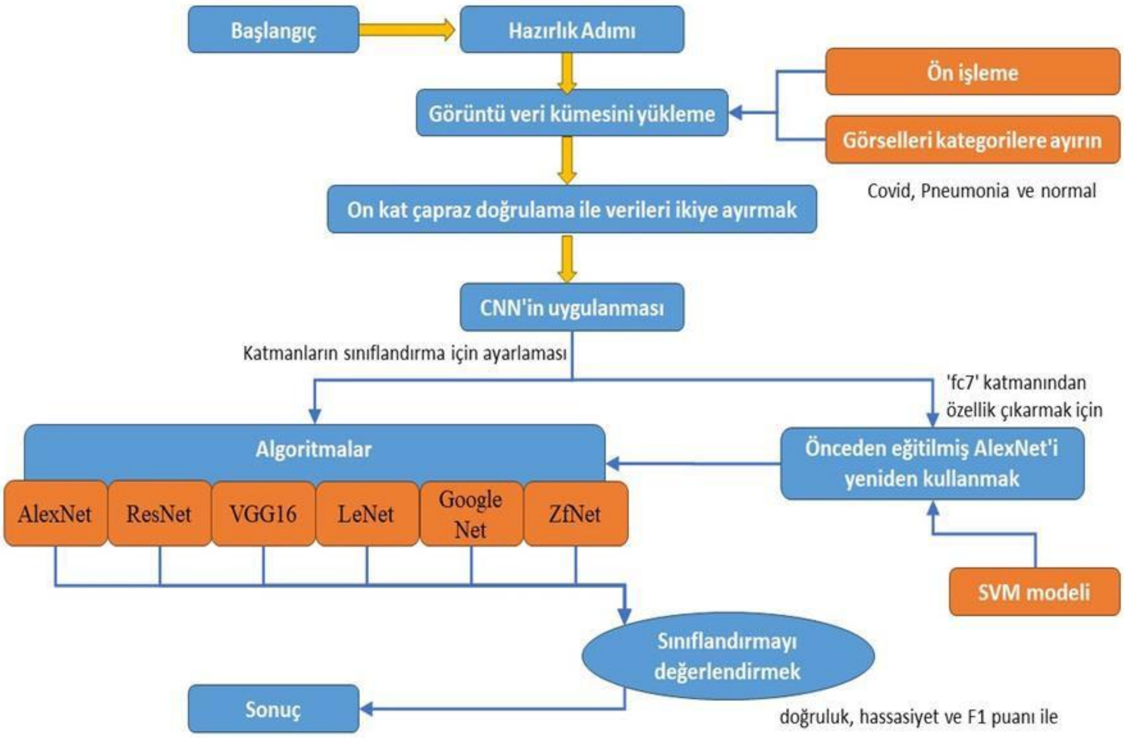
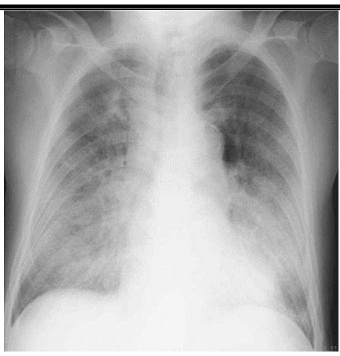
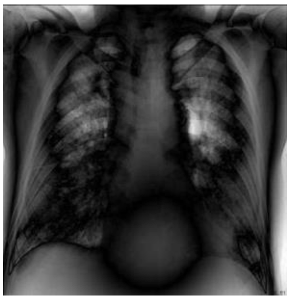
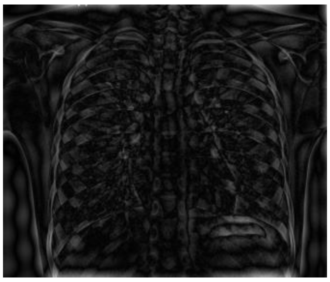


Figure 3.1: Concept of the proposed model

Lung disease	***Original image***	***Deep features***
COVID 19		

PNEUMONIA		
NORMAL		

It was decided that the AlexNet model would be the most important component of the new model. Our goal is to build the model using a very efficient model, so we decided to use AlexNet instead of any pre-trained model. Two different ideas that leverage the AlexNet-inspired framework of the proposed model. The architecture of the proposed model is very close to the original AlexNet model. The two share the same number of layers, the same number of neurons, and the same size filters.

The AlexNet pre-trained network is loaded and the last three layers of the new classification are tuned by training the network on the training data. The AlexNet pre-trained network is then used to extract features from the "fc7" layer and then classify these features using Support Vector Machine Model (SVM), where these features are extracted from the training and test images. We provide a better framework by evaluating efficiency and accuracy values and introducing batch and maximum normalization as an activation function in AlexNet.

It can be seen from the previous diagram that the model starts with the preparation and initialization step. Initializing the model by fetching the necessary libraries, naming the parameters, and also editing the basic settings is the most important step in creating an integrated model. It is possible to benefit from the suggestions of previous researchers in the method of selecting the properties and layers of networks to achieve the results that characterize the proposed method.

The system's data set is loaded in the next step. It is the selection of the most appropriate data that makes the model ideal for this purpose. The system, created based on data for the diagnosis of a specific disease, can be used by people interested in that disease. The images in the dataset are fetched. This step involves preparing the images with an intermediate step. Image formatting involves resizing, editing, and removing unnecessary images. What increases the efficiency and accuracy of classification in that model is the accuracy of the images included in the model. Ready-made images are entered into the system and the performance of a particular model is compared with the performance of a model that does not use that step with the presence of an image preparation step.

Image titles are added in the next step. Each image in the dataset has its own address. Images can be parsed under three labels (Covid, Pneumonia and normal). Images, along with their titles, are saved in the form's input image variables. This step precedes the step of splitting the data into training and testing sets. Headlines and images are collected and then a 30:70 ratio is adopted to split the data. Most of the data is used to create the system. The other part is used to test the efficiency of the system. The accuracy of the data and the model can be learned through the verification process.

The most important step in the model is the transfer learning CNN mapping step. Layers are created and networks are structured by preparing typical layers and variables for the optimization function and the amount of hidden layers. AlexNet pre-trained network was loaded, and this network was used in two stages, being the most important network in the proposed model scheme. The last three layers of the new classification are tuned by training the network on the training data. The last three layers of the AlexNet network are responsible for training the model based on image addresses. The network used in the model can distinguish images and extract features from the images.

A pre-trained AlexNet network is reused to extract features from the “fc7” layer. The extracted features are used in classification and the classification is done using Support Vector Machine Model (SVM). The process of building the network and extracting these features from training and testing images is the function of the AlexNet custom network, which has been adopted in the model due to its previously proven efficiency

3.2. System Evaluation

Performance is measured using the formula for accuracy (Eq. 1), precision (Eq. 2) and F1 score (Eq. 3):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$F1 - score = \frac{2 \cdot \Pr ecision \cdot \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \quad (3)$$

Nerede:

$$\Pr ecision = \frac{TP}{TP + FP} \quad (4)$$

$$\operatorname{Re} call = \frac{TP}{TP + FN} \quad (5)$$

• True Positive (TP): The number of correctly classified data indicating the correct status.

• False Positives (FP): The number of incorrectly categorized data that is not indicative of the correct case.

• True Negative (TN): The number of data that is not correctly classified as a case and is not indicative of a case.

• False Negative (FN): The number of data that are not correctly classified as a case and are indicative of a case.

3.3. Obtained results

AlexNet's training process is applied by fine-tuning the last three layers of the network. Training was stopped after 6 hours in the 440th iteration of the 2nd period due to lack of hardware resources. Figure 4.2 shows a training iteration where output accuracy approaches 100%, demonstrating the effectiveness of the training procedure

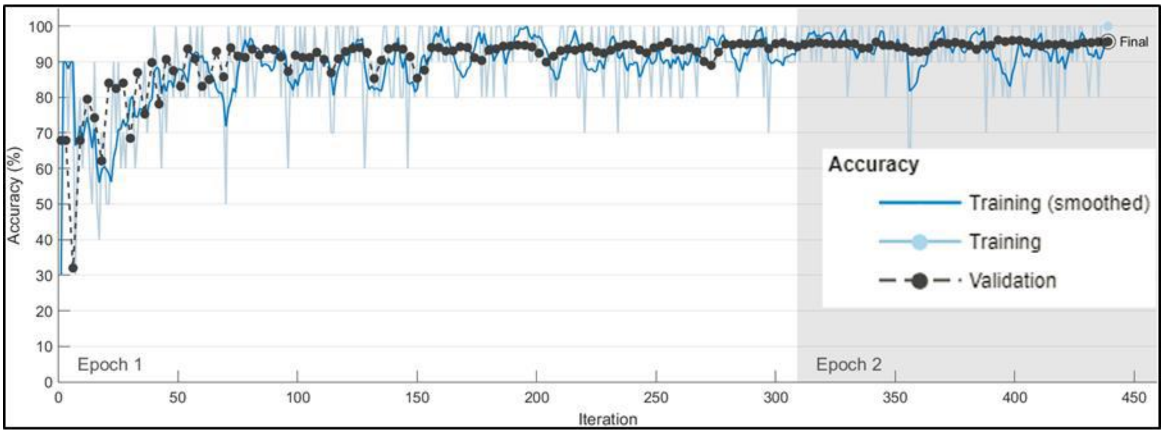


Figure 3.2: Training process and progress of AlexNet

The detailed performance of the training and testing procedures is shown in (Table 3.1). The accuracy of AlexNet's training is equal to 96.76%, and the accuracy of tests reaches 95.5%. The sensitivity of the Covid and pneumonia classification exceeds 98 percent, but in the normal category, this rate is around 90 percent. An F1 score above 97% indicates that the AlexNet classifier produces a low number of false positives. For a more detailed understanding, the test results are shown using a confusion matrix in (Figure 4.3); Here we can notice that AlexNet classifier has a big confusion between pneumonia and normal lung images. ResNet50 performed best with 97.76% accuracy and 99.76% precision.

	AlexNet			**ResNet50**			**VGG16**		
	COVID 19	***NORMAL***	***PNEUMONIA***	***COVID 19***	***NORMAL***	***PNEUMONIA***	***COVID 19***	***NORMAL***	***PNEUMONIA***
Kesinlik (%)	96.76			97.76			97.21		
Duyarlılık (%)	98.59	90.51	98.62	99.76	91.87	99.76	99.12	91.15	99.22
F1- Puanı (%)	97.38	93.56	97.71	98.87	94.76	98.66	98.26	94.17	98.32

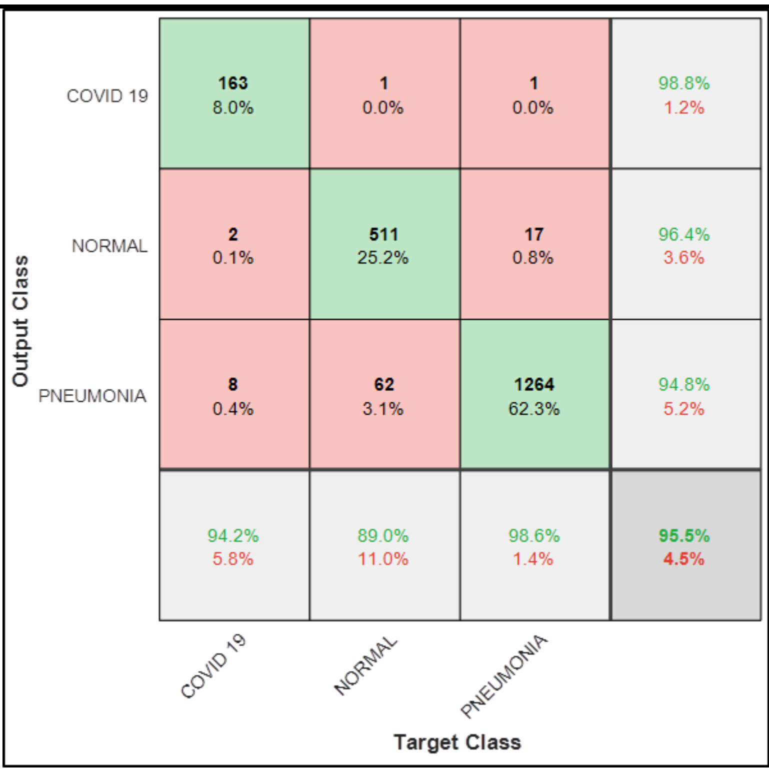


Figure 4.3: Confusion matrix of classifying the test dataset with AlexNet network classification

Classification performance of the SVM model, where the input is features extracted from images using the AlexNet network. Detailed performance of the training and testing procedures is shown in (Table 4-2). The accuracy of training the SVM model exceeds 99.9%, and the accuracy of tests reaches 95.2%.

The sensitivity of the Covid and pneumonia classification exceeds 98 percent, but in the normal category, this rate is around 90 percent. An F1 score above 96% indicates that the SVM classifier produces a low number of false positives. The test results of the SVM model (Figure 4.4) are shown using a confusion matrix with increased sensitivity to detect normal and Covid cases. ResNet50 performed best with 99.53% accuracy and 99.65% precision.

Tablo 4.3: LeNet,GoogleNet, ve ZfNet ağlarının sınıflandırma performansı

	LeNet			**GoogleNet**			**ZfNet**		
	COVID 19	***NORMAL***	***PNEUMONIA***	***COVID 19***	***NORMAL***	***PNEUMONIA***	***COVID 19***	***NORMAL***	***PNEUMONIA***
Kesinlik (%)	82.31			87.23			88.19		
Duyarlılık (%)	82.56	76.8	83.79	92.15	94.82	93.4	87.19	84.41	81.73
F1- Puanı (%)	81.53	75.79	82.82	92.98	94.51	92.72	88.29	80.06	90.63

Figure 4.5: Confusion matrix for classification with other networks classifier

We present performance measurements of three different neural network architectures (LeNet, GoogleNet, and ZFNet) that act as classifiers in the medical imaging classification task to identify COVID-19, Normal, and Pneumonia cases. Accuracy values reveal the overall effectiveness of each model in correctly classifying samples. LeNet achieves an accuracy of 82.31%, while GoogleNet and ZFNet exhibit higher accuracies of 87.23% and 88.19%, respectively. Sensitivity metrics, which represent the ability of models to accurately detect positive cases, provide insights into the performance of models for each class. In particular, GoogleNet outperforms both LeNet and ZFNet in this regard, showing high sensitivity for COVID-19 (92.15%), Normal (94.82%), and Pneumonia (93.4%). ZFNet also shows competitive accuracies in all three classes. Additionally, the F1 score, a metric that balances precision and recall, underscores the overall efficiency of each model.

GoogleNet stands out with its high F1 scores for COVID-19 (92.98%), Normal (94.51%), and Pneumonia (92.72%), reflecting its strong performance in striking the balance between precision and recall. While LeNet and ZFNet exhibit lower overall accuracy, they still maintain competitive F1 scores, highlighting their benefits in certain aspects of the classification task. In summary, GoogleNet exhibits superior performance in terms of accuracy, precision, and F1 score, making it particularly effective at this medical imaging classification task. While LeNet and ZFNet achieve lower overall accuracy, they still perform competitively on specific metrics and showcase the subtle strengths of each architecture in the context of the task at hand.

Figure3.3: Confusion matrix of classifying the test dataset with AlexNet network classification

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The main purpose of this study is to examine the effectiveness of AlexNet as a direct classifier and feature extraction stage in medical image classification using deep learning and transfer learning. (Figure 4.5) shows that AlexNet outperforms the SVM model with 95.5% accuracy after training its last three layers on the target dataset. On the other hand, SVM classifier shows better precision and F1 score; this reflects the fewer false positives and negatives of the SVM classifier. As for the computation time, the training process of AlexNet can take from hours to days, but as a direct feature extractor that does not require training, AlexNet usually requires a few seconds or minutes maximum. ResNet50 model shows the best performance with 99.53% accuracy.

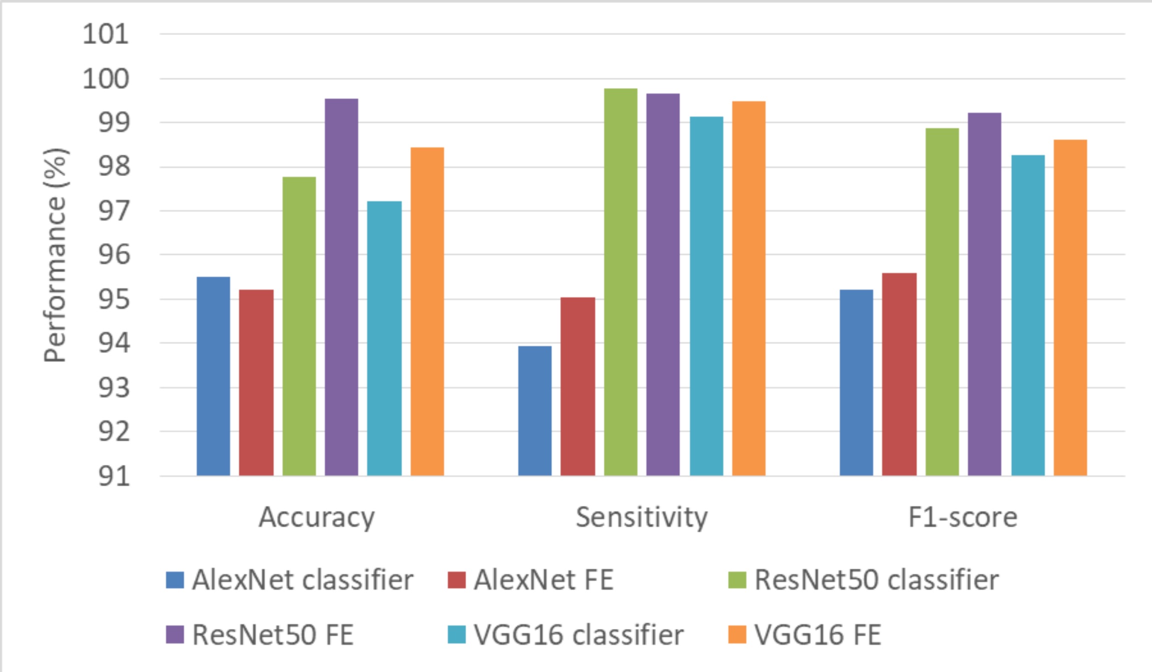

Figure 3.4: Classification performance of AlexNet, ResNet, VGG16 and SVM classifier

Like the resulting registrations and resulting scores, the SVM classifier has lower false positive and false negative rates, measured by precision and F1 score. While AlexNet's training procedure can take hours or even days to complete, using AlexNet directly as a feature extractor without training usually only takes a few seconds or minutes.

II. CONCLUSION (10 BOLD)

In this work, we propose a new approach to classify medical images into three categories using deep convolutional neural networks. We evaluated the performance of our proposed models using several commonly used metrics, including accuracy, precision, and F1 score. Our experimental results showed that the proposed models showed significant accuracy with the proposed AlexNet approach to improve the overall performance. AlexNet is used at two levels in the model and is relied upon to provide a more accurate model to stakeholders and decision makers.

To distinguish our proposed idea, the performance of the AlexNet model was compared with two other networks, ResNet and VGG. Comprehensiveness has been added so that the same experiments can be performed with different models, which helps to obtain the most accurate results. The results of our experimental evaluation show that the proposed models based on AlexNet hold significant promise in providing accurate and rapid diagnosis of COVID-19 using CT scans. This conclusion is supported by the results of our experiment. To further improve the accuracy and efficiency of COVID-19 diagnosis, future studies may explore the possibility of extending our proposed models to other medical imaging tasks or combining our method with other diagnostic tools. Both of these options are open to exploration. Cross-sectional medical photographs can be used to distinguish patients and compare injuries by adding the names of various conditions. In addition to choosing a classification mechanism, the model can be made more accurate as follows.

In a referenced study [58], researchers used three convolutional neural network models (ResNet50, InceptionV3, and Inception-ResNetV2) to detect coronavirus pneumonia in COVID-19 patients through chest X-ray images. The models achieved high accuracy rates of 98% for ResNet50, 97% for InceptionV3, and 87% for InceptionResNetV2. There was no need for feature extraction or selection, and the models were applied approximately 30 epochs during training to avoid overfitting. It is important to note that the work utilized a limited number of available images at the time. Using digital x-ray images, researchers [59] were able to distinguish COVID-19 from pneumonia patients with 98% accuracy. They did this using four different neural networks pre-trained on other images. These networks included: ResNet18, AlexNet, SqueezeNet, and DenseNet201. After training these models using a 20x set of images as input, they used image augmentation (rotation, scaling, and transformation) to increase the accuracy of the detection process. Researchers have developed a dataset of CT scans to aid in the detection of COVID-19 [60]. The dataset contains 275 positive CT scans and 195 negative CT scans for COVID-19. They used this dataset to train a deep CNN model specifically designed to identify the presence of the virus. However, due to the limited size of the dataset, they used transfer learning by pre-training the deep CNN model on a larger collection of chest X-ray images. They fine-tuned this pre-trained network using the COVID CT dataset and applied data augmentation techniques to increase the size of the training data. The accuracy achieved was 84.7%. Another study [61] proposed a rapid COVID-19 diagnostic method using artificial intelligence. Researchers applied CNN to CT images of 108 patients with laboratory-confirmed COVID-19 and 86 patients with pneumonia. Multiple deep learning methods were used, and ResNet-101 achieved the highest accuracy of 99.51% in distinguishing between COVID-19 and pneumonia. In this study, we introduce Alexnet-SVM and other models as a tool for detecting and diagnosing lung diseases in the human lung system. This innovative architecture was specifically designed to classify the most common chest conditions, including COVID-19, pneumonia, and lung cancer. To evaluate the performance of various models, we compared their accuracy and F1 scores. The results show that the Alexnet-SVM model exhibits the highest classification performance with an accuracy rate of 95.22%. The reason for the difference is that the authors of these studies evaluated their models solely on the basis of accuracy, whereas our evaluation takes additional factors into account.

shows off his talent. Sensitivities vary between classes; GoogleNet exhibits strong capabilities, and F1 scores consistently demonstrate GoogleNet's balanced precision and recall. These findings position GoogleNet as the most effective model that excels across many performance metrics in the context of medical image classification.

Comparing our results with reference works [58–61] focusing on COVID-19 detection in chest X-ray and CT images, where various neural network architectures achieved accuracy ranging from 87% to 99.51%, our work introduces Alexnet-SVM et al. models. Designed to detect common chest conditions including COVID-19, pneumonia, and lung cancer, the Alexnet-SVM model demonstrated the highest classification performance with 95.22% accuracy.

In conclusion, our work highlights the importance of a comprehensive evaluation approach that considers multiple metrics and factors when evaluating the performance of neural network architectures for medical image classification tasks. While GoogleNet stands out as the preferred choice among LeNet, GoogleNet, and ZFNet in our specific task, the comparison highlights the complexity of model evaluation and the need for a nuanced understanding of performance metrics in various medical imaging contexts.

In our research on chest X-ray and medical image classification using three different neural network architectures (LeNet, GoogleNet, and ZFNet), we present the performance metrics in Table 6 . These metrics include accuracy, precision (recall), and F1 scores across three different neural network architectures. classes: COVID-19, Normal and Pneumonia. In particular, GoogleNet demonstrated its superiority in accurately classifying chest X-rays, performing better with a top accuracy of 96.23%.

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