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Medical Image Processing using Deep Learning Techniques in Big Data Perspective

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Abstract— Artificial intelligence and machine learning will be the driving forces behind the next computing revolution. These technologies rely on the ability to identify trends from historical information and predict future outcomes. One of the best machine learning techniques, deep learning is employed in a variety of applications, including object recognition, picture categorization, image analysis, and clinical archives. Image and video data are necessary for both diagnosing the patient's illness and determining its severity. Convolutional neural networks are efficient gears for digital picture classification and image understanding. The production of medical photographs has ex-ponentially increased as a result of the proliferation of digital devices and the development of camera technology, which creates Bigdata. Massive, difficult-to-manage volumes of structured, unstructured data are referred to as "Big data". The more data processed for analysis, the greater will be the analytical accuracy and also the greater would be the confidence in our decisions based on the analytical findings. In this paper, we proposed a novel method for early detection of pneumonia disease using deep learning techniques along with the big data storage and big data analytics to achieve more better performance. The results show that, the model achieved 91.16% of accuracy and 93.22% of F1-score.

Keywords- Big Data Analytics; Machine Learning; Convolution Neural Networks; Deep Learning; Medical Image Processing.

I. INTRODUCTION

Big data analytics is the process of using state-of-the-art analytical techniques to very large, heterogeneous data sets that include structured, semi-structured, and unstructured data. These data sets can range in size from terabytes to zeta bytes and come from a variety of sources. Big data refers to data collections that are either too large or have a distinct structure for standard relational databases to adequately capture, manage, and handle. Big data is distinguished by its enormous diversity, huge volume, and rapid velocity. Because of new data sources and formats including the Internet of Things (IoT), smart phones, social media, and Artificial Intelligence (AI), data complexity is rising. Devices, networks, log files, transactional apps, internet, and social media web sites and apps often produce enormous amounts of data. Big data analysis assists analysts, academics, and business users in fast reaching better decisions by utilizing data that was previously unavailable or improper. By merging their present corporate data with modern analytics techniques like text analytics, machine learning, predictive analytics, data mining, statistics, and natural language processing, businesses can uncover new insights from previously untapped data sources.

In order to forecast future, unforeseen data, machine learning pays special attention to learning patterns based on the raw data. The efficiency of artificial intelligence algorithms depends critically on the quality of the input data. Pre-processing is necessary in theory to turn the raw data into a good representation of the data by removing salient features to identify patterns in yet-to-be-observed data. It's called "feature engineering.". The use of feature engineering significantly reduces the complexity of high-performance machine learning models.

Big Data has become more crucial for major corporations like Google, Microsoft, IBM, and Amazon as a result of Moore's Law, which states that the world's data doubles every year. Big Data is one of the key high-focus areas of data science. Big Data is associated with 5V's concept as shown in Figure 1.

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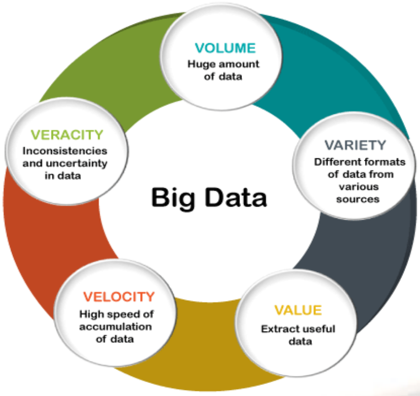

Figure 1. Big data characteristics

Volume: Big data refers to the large amount of information generated daily from multiple sources, including business operations, machines, social media platforms, networks, human interactions, and many others. A million messages can be created in the face book, the "Like" button has been pressed 4.5 billion times, and more than 350 million new messages are added every day. Big data methods can process large amounts of data.

Velocity: The pace at which data is collected is referred to as velocity. This is mostly due to the Internet of Things, mobile data, social media, and other causes. In 2001, Google received 38.9 million requests daily. Google received 11.3 billion searches daily in 2021.

Variety: Variety refers to data that is organized, semi-structured, or unstructured as a result of different data sources used by people or machines. Data is gathered in a variety of formats, like PDFs, emails, audio files, social media postings, photographs, and videos.

Veracity: Veracity refers to how reliable the information is. It can filter or transform data in a number of ways. Verity is the ability to effectively process and manage information. Because of the data coming from variety of sources, we must verify its' accuracy before using it for business analysis.

Value: Value is an important part of big data. We do not process or store data. We also store, process and evaluate accurate and valuable data.

In recent years, among the most popular subjects of scientific debate has been big data. The technique of analyzing this vast amount of data to find any hidden patterns or links is known as big data analytics. Big data analytics has demonstrated its value in a number of industries, including research, sports, and advertising. It has also been used in medical procedures, assisting with the delivery of care and the study of diseases. To get relevant results, researchers have been utilizing massive amounts of pictures, signals, and genomics data, either separately or by merging data from several sources.

As new techniques are created and the effectiveness of treatments is tracked, the use of technology in medicine has significantly risen over the past few decades. Interdisciplinary research on the analysis of medical imaging has completely changed the capabilities of contemporary healthcare professionals. We have increased the development and usage of computer-aided medical diagnostics and decision support systems as a result of the high number of healthcare organizations and patients. Analytics for medical images enhance the contents' ability to be comprehended.

Techniques for gathering, distributing, and compressing medical imaging data are crucial in addition to analytical methods. The majority of the difficulties in doing an analysis of medical imaging are common to any big data analytics. Nevertheless, multiple additional procedures are required, mostly since each analysis data collection method. High dimensionality and frequently huge sample sizes are characteristics of big data, which pose a number of unique problems such as noise accumulation, erroneous correlations, unintentional homogeneity, computationally expensive models, and algorithm instability. Many techniques and methods perform well for moderately sized datasets, but they are unable to handle the dimensionality's rapid increase.

II. RELATED WORK

CNN, a deep learning-based technology that classifies images by using networking models on health data is proposed in [1]. Today, the major application of health data cardinal pictures is to swiftly and properly diagnose any illness that occurs in a patient by fast and simply identifying it. Machine learning models such as the neural network-based ANN model, were implemented in this paper. Some supervised machine learning approaches are contrasted using hybrid features and other methodologies, in which hybrid features with the SVM model and SoftMax features are delivered with greater accuracy than the other models.

Classification of images that uses the deep learning algorithm is proposed by [2]. Spam detection and image categorization are both done using the deep learning method. In this paper many datasets were taken into consideration and CNN algorithm is used for images for the purpose of classification. By using graphical representations of the images, the methods were applied to other types of datasets. The experimental findings were determined using Mean square error values, demonstrating that the Convolutional neural network technique produces accurate results that represent images very well and with a low error rate, overall CNN performs superior on all datasets utilized in this paper.

Detecting the chest x-ray images using multiple CNN models are proposed in [3]. X-ray images are mostly used in the present days in every field for the treatment of patients. In order to provide medical treatment to patients, a large number of x-rays must be checked by the doctor, who must then

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provide an accurate conclusion for each and every report, requiring the use of many pictures detection and synthesis methods. As population increases, more people are currently afflicted with numerous diseases, with diabetes, heart issues, etc., becoming the most prevalent problems for everyone. In this research, multiple CNN model is used to identify the chest x-rays from the dataset and locate which are not in a good condition, which is to say which are in abnormal condition. The CNN method is typically used in deep learning models in order for multiple CNN to function.

Non-medical training on deep learning approaches for predicting chest pathology are reported in [4]. In the chest x ray, there are certain disease that are need to be identify such that some of the bloods were need to be collected and based on the many things' doctors come to a conclusion and identifies the solution for the problem. Present chest x-rays were considered from the dataset which consists of 433 images. CNN method with deep architecture classification proves with greatest accuracy of the model when several deep learning model's algorithms are applied for the dataset on non-medical photos that identify various sorts of diseases that are included in the dataset.

The Deep Gru is suggested [5] for the detection of chest x-rays Covid-19 data with the CNN model. In the present scenario covid 19 has become the dangerous disease and needs to be take treatment in an early time such the patient cannot get harmed and becomes out of danger. As long as the sickness is present in the human body at the time of death, it is possible for virus-infected persons to be diagnosed with the disease, many algorithms were taken, and different experiments are conducted on the covid 19 data. The chest x-rays of patients with pneumonia, healthy patients, and patients who have been infected with the COVID 19 virus are used as training data for the CNN deep learning model, which is discussed in this study. The models such as CNN with hybrid deep learning and gated recurrent unit produce the maximum performance in detecting the photos out of the total 424 that are obtained from the chest dataset.

Classification of disease using CNN on Chest X-Rayis proposed in [6]. As technology advances, it is becoming increasingly important to use chest x-rays to diagnose the patient's illness. As a result, numerous techniques are employed to improve the model's accuracy and predict the correct outcome. CNN is now the model of choice for diagnosing all diseases, but it also plays a significant role in the classification of images in research papers. The chest dataset is derived from health data and was collected through online tools like Kaggle. It contains information on fourteen different ailments, seven of which were found using a technique called the multi-label classification.

Classification of diseases based on the Convolutional neural network study of tooth x-ray images is mentioned in [7]. Many algorithms are used for classifying the X-ray images in deep learning technique the mostly one is CNN technique, In the medical field tooth is also a problem that the people are suffocated more with more pain not only in children irrespective of their age groups the people will be facing these problems. Some home remedied can reduce the problem but some will be getting the major problem who are having the less immune system. In this paper some of the tooth occurring problems patients' x rays were collected and some problems were identified among those few are facing abnormal teeth, implants, etc., there four sub parts the diseases of x-rays are considered in which deep learning technique is used to classify the problem and achieved the accuracy and the model performs very well for tooth data.

Classification of Chest X-Ray Images using CNN for feature extraction to detect Pneumonia is given in [8]. When people are exposed to this form of contamination, their lungs are seriously damaged. The patient suffers from a severe cold and is unable to endure the ambient conditions when there is heavy cool. To detect this virus in its early stages, chest x-rays are required to determine how seriously the infection has damaged the patient in the deep learning model. The Convolutional neural network model is used to detect the chest x-rays and features are taken from them to determine if the patient has pneumonia or not. The results are quite convincing.

Deep CNN architectures are proposed [9] that use transfer learning and medical picture analysis. The CNN algorithm, which is the module of the deep learning approach, has been studied more and more in the healthcare profession. Nevertheless, since hospitals mainly use it to diagnose patients, collecting evidence from a natural image is a better option than extracting features, making the process more difficult. As a result, the results of the fine-tuning process are different from those of previous design.

A new multimodal medicinal image fusion method for overcoming a wide range of medicinal diagnostic challenges is addressed in [10]. This method employs the energy attribute fusion and boundary-measured pulse-coupled NN fusion approaches in a non-sub-sampled transform domain. The strategy was validated by the researchers using a dataset of over 100 picture pairings from diverse disorders, including metastatic Cancer and Glioma.

A self-training strategy based on a repeated labeling approach to address the mislabeled instance issues because they hinder the classifier's performance [11]. This study retrieved the features that had a higher relation to the classification result in order to manage medical data. In order to enlarge the training set in accordance with the domain expert's experience, the unlabeled medical record data is afterwards selected with high confidence. The tri-training model's classifier, which uses a supervised learning model to train three fundamental classifications, is then tuned for performance.

Various deep learning models used in detecting and classifying lung cancer disease are compared [12] and concluded that deep learning can speed up the detection of whole section images (WSI) and also matching with the detection rate of pathologists.

The interested area from the dataset named chest x-ray--14 using segmentation method is extracted [13]. The experiments conducted on the dataset and achieved 92% of mean accuracy. Radiographs are considered and trained using machine learning with the fuzzy tree transformation [14]. To extract the features a multi-kernel model and then a classifier is used and the accuracy achieved was 97.01%.

The ability of the modified CNN to categorize pneumonia disease and differentiate viral and bacterial infection in pediatric chest X-Rays [15]. It is difficult to categorize pneumonia due to a number of characteristics that are unrelated to the diagnosis of pneumonia from chest X-Rays. CheXNet performed classification of thoracic disease using chest X-rays which strike human vision.

A modified method (CMixNet) based on two deep, tailored three-dimensional mixed link networks for the classification and identification of lung cancer is developed [16]. The CMixNet module's properties were used to classify lung nodules using a gradient boosting machine (GBM). The results of the nodule-based deep learning classification were compared with a variety of factors, including the patient's age, family history of cancer, history of smoking, location and size of the discovered nodule, and clinical biomarkers.

Deep convolution neural network has been proposed as a deep learning approach for dermatologist-level classification of malignant lip disorders [17]. The dataset consisting of 1629 clinical images was used for training the ResNet model. The effectiveness of the suggested strategy was assessed using several sets of photos that contained 281 and 344 instances. For classification purposes, the suggested model is compared with 44 participants. A novel 3D-DSC (3D-DSC) module for the analysis of volumetric medical images is given in [18]. In this study, 3D-DSC is used in place of the conventional 3D convolutional kernels. The 3D-DSC architecture is built utilizing a number of 1D-filters that are closely spaced together.

A deep learning system was published for the validation and development of numerous abnormalities findings in retinal fundus pictures [19]. The earth movers distance (EMD) method is used to discriminate between infected and uninfected lungs [20]. All non-lung regions are removed from the raw image after preprocessing. After the image has been preprocessed, it is scaled and normalised by intensity to provide a set of uniform lung sizes and shapes. The existing and forthcoming issues in medical image processing were identified [21]. A number of studies regarding the usage of deep learning methods in the finding of various diseases are highlighted in [22]. EvoCNN [23] offers a GA-based method that represents the CNN model's constituent parts using a variable-length gene encoding scheme. To evolve the architectures of CNNs of any length, a new hybrid differential evolution (DE) technique with a recently added crossover operator is proposed [24]. This approach is known as DECNN.

To improve the fluidity and descriptiveness of the generated image captions, [25] proposed a hierarchically trained deep network. Initial regional proposal generation and two crucial steps for the creation of picture descriptions are the important stages in the proposed deep network. To secure the network for the accurate prediction of brain tumours, such as pituitary tumours, meningioma tumours, and glioma tumours, [26] proposed convolutional neural network model, an existing block chain-based method is employed. After being normalized in a fixed dimension, brain MRI data are initially placed into pre-trained deep models. To extract the characteristics from a convolutional neural network designed for deep brain magnetic resonance imaging scans, the researchers in [27] used transfer learning. A two stage hybrid image segmentation method is developed [28], The DOBES optimization technique is employed for multilevel thresholding in the first stage. The morphological techniques have been used in the second step to remove the undesired area present in the segmented image after the thresholds for image segmentation have been chosen.

III. METHODOLOGY

A. Building blocks of Convolutional Neural Network

Traditionally, simple machine-learning models or manually constructed features derived from the raw data are used to train machine-learning models to carry out useful tasks. Deep learning avoids this laborious and tedious phase by having computers automatically discover meaningful representations and characteristics from the raw data. There are alternative deep learning models, but artificial neural network variations are by far the most used. The emphasis on feature learning, or autonomously discovering data representations, is the major commonality amongst deep learning approaches. This is the primary distinction between deep learning and other "traditional" machine learning techniques. Characteristic discovery and task completion are combined into a single challenge, and hence both are improved during the same training session.

Convolution Neural Networks (CNNs), is a powerful approach for learning meaningful representations of pictures and other structured data, have attracted attention in deep learning in the field of medical imaging. Traditionally, these properties had to be hand-engineered or produced by less capable machine-learning models before CNNs could be used effectively. Previously, these attributes had to be hand-coded or generated by less capable machine-learning models. Many of the manually produced image attributes were frequently dropped. Previously, features learned directly from data could be used since feature detectors discovered by CNN were practically meaningless. When we analyze the strong preferences that are built into CNNs, we may better understand why they are so effective.

B. CNN Methodology

The conventional feed forward neural networks described above can potentially be used to apply neural networks to photos. However, it is incredibly wasteful to have connections among each node in one layer and every node in the following. Using domain knowledge like image structure to prune the connections improves performance dramatically. CNN is a sort of artificial neural networks with very few connections between the layers that is designed to preserve spatial correlations in the data. Each layer action in the CNN works on a small area of the preceding layer, with all the input organized in a pattern and passed through layers that maintain these relationships. CNNs have the ability to produce a very effective graphical representation of the supplied data.

1) Convolution layers

A tensor of feature maps is created when a Convolution layer is applied to all of the Convolution filters at every input point. Convolution layers combine the activations from the preceding layers with a number of tiny parameterized filters, frequently of size 3 X 3, and store the results in a tensor W(a,b), where a is the number of the filter and b is the layer. If each filter has exactly the same weights over the entire input domain, or a translation equivalent in each layer, the number of weights to be trained can be greatly reduced. This weight sharing is necessary since it is likely that items in one section of the image will also appear in another. For instance, if we have a filter that can recognize basic shapes, we may use it to identify those shapes everywhere it appears.

2) Activation function layer

The output of convolution layer called as “Feature maps” are provided as input to a non-linear activation function. As a result, virtually any non-linear function may be approximated by the neural network as a whole. Leaky ReLUs, parametric ReLUs, or very basic rectified units, often known as ReLUs, are frequently used as activation functions (0, z). The feature maps are fed into an activation mechanism to create new feature maps.

3) Pooling

After the input has been fed through one or more convolutional layers, each feature map is then passed through the pooling layer. It produces single integer for every region from the input of small grid regions. The average function or the max function, commonly referred to as max-pooling, is typically employed to calculate the number (average pooling).Using convolutions with longer strides is another method for obtaining the pooling’s down sampling effect. The network architecture is made simpler by eliminating the pooling levels without necessarily compromising performance.

4) Dropout Regularization

It is a fundamental concept that significantly improved CNNs' performance. One typically achieves higher performance when employing an ensemble of models rather than a single model. An averaging method is called "dropout" which is based on a stochastic sampling of neural networks. From the input of small grid regions, pooling procedures generate single integers for each region. In most cases, the average function or the max function, also known as max-pooling, is used to calculate the number (average pooling). The pooling layers provide the network some translational invariance because a minor adjustment to the input image causes a slight modification to the activation maps.

5) Batch Normalization

This is often used after activation layers, and they produce normalized activation maps by dividing each training batch's activation maps by the standard deviation and subtracting the mean. By including batch normalization layers, training is speed up, the network becomes more regular, and it is less reliant on precise parameter initialization. As the training batch reaches these layers, the network is frequently compelled to change its activations to zero mean and unit standard deviation.

6) Image Classification

These components are merged in increasingly intricate and interrelated ways in the creation of new and superior CNN architectures, or are even replaced by other more convenient activities. There are several things to think about while designing CNN to do a specific task, such as comprehending the problem to be solved and the needs to be met, determining the best way to feed data to the network, and making most use of one's budget for compute and memory usage. Early on in the development of contemporary deep learning, one tended to combine the building pieces in very basic ways, as in Lenet and AlexNet. Later network architecture is significantly more complicated, and as a result, the state-of-the-art has been updated. Each generation builds on the concepts and insights from earlier architecture.

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C. Design

The performance of the network will be greatly influenced by how the convolution process is used, which is the foundation of CNN. Anything bigger than 3x3 isn't really useful for CNN; Sequentially stacking 3x3 convolutions will successfully attain the same receptive field as a bigger sized convolution while being more computationally efficient, as has been repeatedly demonstrated, most notably with VGGNet and ResNet. The sample CNN architecture for image processing is shown in Figure 2 and its convolution operation is depicted in Figure 3.

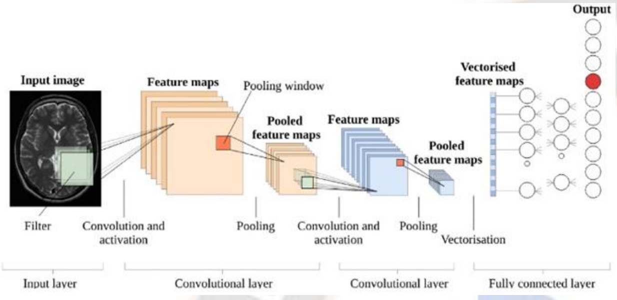

Figure 2. CNN Architecture.

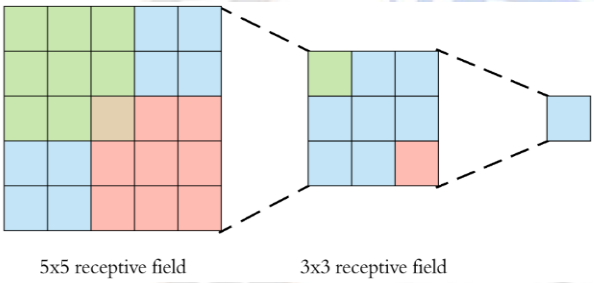

Figure 3. The Convolution operation.

To minimize the dimensionality of the feature maps before processing with a 3x3, the 1x1 convolutions can also be used at certain points in the network. With the bottleneck block depicted in Figure 4, ResNets accomplished this. We initially consolidate all the data into 64 feature maps rather than processing a massive 256-deep feature map. We apply our 3x3 convolution after it has been compressed; it is much faster when applied to the 64 feature maps rather than the 256, and such processing has been demonstrated to yield the same or better results than just ordinary stacks of 3x3s. Finally, using another 1x1, we map back to our original 256 size.

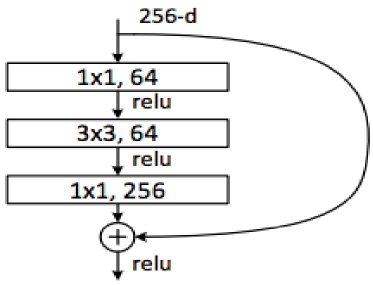

Figure 4. Relu function.

A. Pooling

In the CNN, down sampling is employed as we move deeper into the network, while pooling is used for feature summarization. Our ability to retain spatial information will be lowered as a result of the down sampling when we reach the end of each "stage" and wish to downgrade sample. As a consequence, we pool our information in order to summarize it and keep it safe. The two most popular pooling techniques are Max and average.

The scientific community is still split on whether max or average pooling is preferable. Sincerity be told, I've found the difference to be incredibly small. To hold onto the best features, a popular approach is to employ max pooling throughout the network, and then average pooling at the very end to obtain a final vector representation of your features before deploying the final dense layer and handing things off to the SoftMax function.

B. Preprocessing and Enhancement

The pre-processing, augmentation, and preparation of the data are important but frequently overlooked factors. This is not usually necessary. You should determine whether your application would genuinely benefit from any data processing before beginning.

For instance, the common practice in image classification is to mean-normalize the images using the mean of the training data. Research literature has amply demonstrated the value of mean normalization as the industry standard.

Mean-normalization, on the other hand, might significantly harm the network and results while doing an image improvement. Really, refraining from mean-normalization would be advantageous for any task that involves very subtle variations in things like texture, color, or appearance rather than significant variances in shape and semantics.

For the sake of simplicity and practicality, employ dropout by default. If dropout doesn't work, consider some of the other options, such as L1 and L2. If all other methods are

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unsuccessful, there can be a discrepancy between your training and test data.

C. Training

There are various optimization algorithms available. Many people claim that SGD provides the most accurate results, which is true in our perspective. Adjusting the learning rate schedule and settings, however, can be difficult and time-consuming. However, while utilizing adaptive learning rates like Adam, Adagrad, or Adadelta is quick and simple, you might not get the best SGD accuracy.

The best course of action in this situation is to use the same "style" as the activation functions: start with the simple ones to determine whether your design is successful, then tune and optimize using something more sophisticated. Since Adam is so simple to use, we recommend starting there. Simply choose a learning rate that isn't too high, usually, it's set by default at 0.0001 and you'll usually get good results.

IV. IMPLEMENTATION

There are 100,000 de-identified chest x-ray images in the NIH Chest X-ray collection. The pictures are PNG files.The NIH Clinical Center provides the data, which is accessible via the NIH download site from the following url https://nihcc.app.box.com/v/ChestXray-NIHCC.

A. Data Augmentation

Some picture augmentation techniques should be used to artificially expand the size of the image training dataset. Image augmentation expands the dataset's size and variety by creating altered versions of the training set's images, which ultimately improves the model's ability to forecast brand-new images.

B. Rescale

Digital images have pixels with values ranging from 0 to 255, where 0 represents black and 255 represents white. To more equitably distribute their contribution to the overall loss, rescale the scales array of the original image's pixel values to be between [0,1]. If not, it is recommended to choose a lower learning rate, while a greater learning rate would be required for images with a lower pixel range because they result in more loss.

C. Shear_range

The shear's alteration is reflected in the image's shape. While stable on one axis, the picture is stretched to certain angle which is known as "shear angle" and is shown in figure 5.

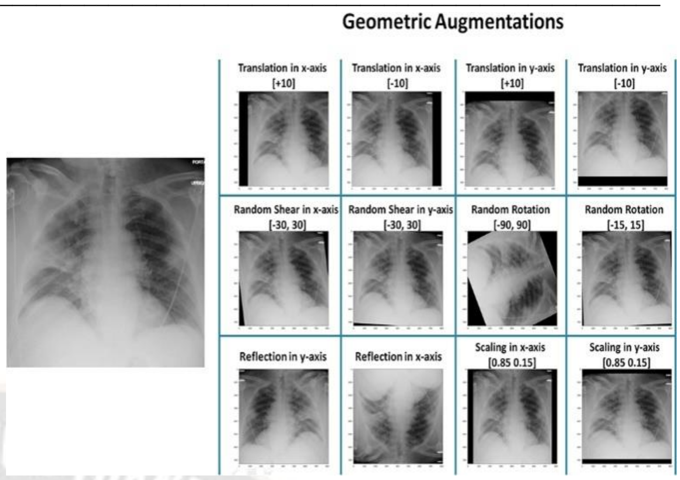

Figure 5. Shearing the Image.

D. Zoom_range

A zoom of less than 1.0 has been used to expand the image. The image has been magnified by more than 1.0 time and is shown in figure 6. Random vertical flip, random horizontal flip, some photos are flipped horizontally, some are flipped vertically and the flipped images are shown in figure 7.

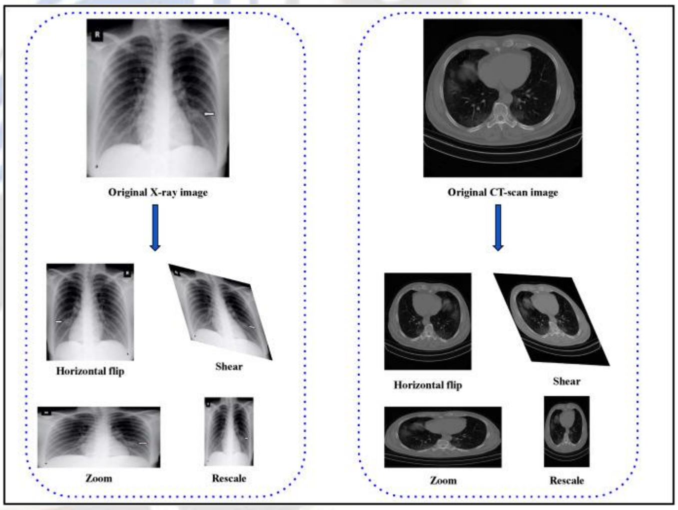

Figure 6. Zooming of the Image.

Technique	Setting
Rotation	45
Vertical Shift	0.2
Horizontal Shift	0.15
Shear	16
Crop and Pad	0.25

Figure 7. Flipped Images

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V. RESULTS AND DISCUSSION

The fundamental component of the CNN architecture is convolutional layering. Data from the image is ingested by the convolution layers, which transform it, and then pass it as input to the next layer in CNN. This process is known as the convolutional operation. It is necessary to provide number of filters in each convolution layer. In the shape of objects, edges, forms, curves, textures, or even colors, these filters search for patterns. It may identify items or patterns with deeper levels that are more complicated. The fundamental component of a filter is an image kernel, which can be compared to a 3x3 or 4x4 small matrix applied to the entire image. We will use the Pooling and Convolution layers to decrease the dimensionality of an input representation (image), down sample it, and maintain the maximum value (active features) in the sub regions binding. The stride in the input matrix is the quantity of pixels crossed. We switch to a one-pixel-at-a-time filter when the stride is 1. The filter is moved 2 pixels at a time when the stride is 2, and so on. A huge image can be shrunk down to a manageable size using larger filters and steps. Always start with a smaller filter setting, like 32, and gradually increase it.

- Build the model by first adding a layer of Conv2D, then another layer of MaxPooling.
- An odd number, such as 3x3, is desirable for the kernel size.
- Although RELU is the most desired activation function, Tanh, and other substances can also be employed.
- Input shape accepts the width and height of an image with the final dimension being a color channel.
- After CNN layers and ANN layers, flatten the input.

SoftMax's activation function should be used for the last layer. For binary classification, use the sigmoid and set the unit to 1 if the issue contains more than two classes. Units are defined as the total number of classes.

Because we already set their height and breadth, the input shape for the photographs is (500,500,1). And the grayscale colour channel is represented by 1, while the RGB colour channel is represented by 3 (none,500,500,1) Since batch sizes can vary, Keras provides an additional dimension here.

The outcome dimensions of the first convolution operation “Conv2d layer” on a 500X500 picture with 3X3 kernel size, stride=1 and dilation=1 by default, and padding set to "true". The operation (500-3+1, 500-3+1) = (498,498) In addition, we defined 32 filters, and the output pattern is now (None,498,498,32)

Now that we have established that the kernel size=2X2 and the strides=2X2 by default, we can apply those definitions to the input of an image with a size = 498X498 to obtain ((498-2/2)+1,(498-2/2)+1)= (249X249)

Without taking batch size into account, The Flatten layer generates a 1D vector from all of the pixels along all of the channel. This reduces the (13, 13, 64) input to (13x13x64) = 10816 values. The parameter value in the first layer is computed as (kernel height * kernel width * input * output * channels) + (output channels), yielding (3x3x1x32)+(32) = 320.

The short-term ReLU, also known as the rectified linear activation function, is a piecewise linear function that, if the input is positive, outputs the input directly; if not, it outputs zero. By addressing the issue of vanishing gradients, the corrected linear activation functions enables the models quickly learn and perform better.

Padding: Output and input sizes should be same. Because of this, it is necessary to pad so that the filter window can stray outside the input map. The filter window remains at a valid location inside the input map, resulting in a filter size - 1 reduction in output size. No cushioning is used.

Splitting the dataset: After completion of process of visualization done through graphs the subsequent step is split the data in the form of train and test such that 70% of data is utilized for training and remaining 30% of data is for testing purpose. To determine the RMSE (Root Mean Square Error), MSE (Mean Square Error), MAE (Mean Absolute Error), “train_test_split” distributes your data in a random manner amongst the training and test sets according to the specified ratio. We used the sklearn package to divide a dataset into training and testing sets after importing it into a pandas data frame.

Compiling Model Build:

Learning Rate: The purpose of stochastic gradient descent during training would be to minimize difference between the actual & predicted values of the training set. The path to reduce involves multiple steps. We used Adam ensemble approach as an adaptive learning rate and it calculates individual learning rates for various parameters.

Loss function: We will use cross entropy to assess training-related losses, because it is a binary classification. If there were more than four classes, categorical cross entropy would have been utilized.

Accuracy: Determine the frequency with which real labels and forecasts match. It will gauge the effectiveness of training and validation as well as loss.

Fitting the model: Early stopping is used to stop the epochs depending on particular metrics and criteria. This could helps in avoiding over fitting of the model. We would stop over here based on the Value loss metric, which must be as low as possible. If a minimal Value loss is obtained, following

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iterations will stop if the Value loss grows in any of the three rounds, according to patience.

When a statistic reaches a plateau, it causes slow down the learning rate. After learning approaches a plateau, models often gain by lowering the learning rate by a factor of 2-10. This call back checks a quantity, and if there is no improvement after a preset number of "patience" epochs, the learning rate is lowered.

Deeper layers or more complex patterns or things are revealed by the process. The fundamental component of a filter is an image kernel, which can be compared to a 3x3 or 4x4 tiny matrix applied to the entire image.To more equitably distribute their contribution to the overall loss, rescale the scales array of the original image's pixel values to be between [0,1]. Figure 8 shows the predicted output of the model.

After the text edit has been completed, the paper is ready for the template. Duplicate the template file by using the Save As command, and use the naming convention prescribed by your conference for the name of your paper. In this newly created file, highlight all of the contents and import your prepared text file. You are now ready to style your paper.

Figure 8. Predicted Output of the model

The model produces predictions in the 0 to 1 range rather than a precise classification of 0 or 1 due to the sigmoid activation function of the last layer. As a result, we designate a label of 0 for all values between 0 and 0.5, and 1 for those values above 0.5. Note that 0 represents a normal case and 1 implies a pneumonia case. From the confusion matrix shown in the figure 9, it is inferred that, total actual normal images=234, in which 190 images are true predictions (Predicted as normal) and 44 are false predictions (Predicted as Pneumonia). Total Pneumonia images =390, in which 379 images are true predictions (Predicted as Pneumonia) and 11 are false predictions (Predicted as Normal). Using above values, performance measures like, accuracy, precision, recall and F1-score are calculated for the model and the results are shown below.

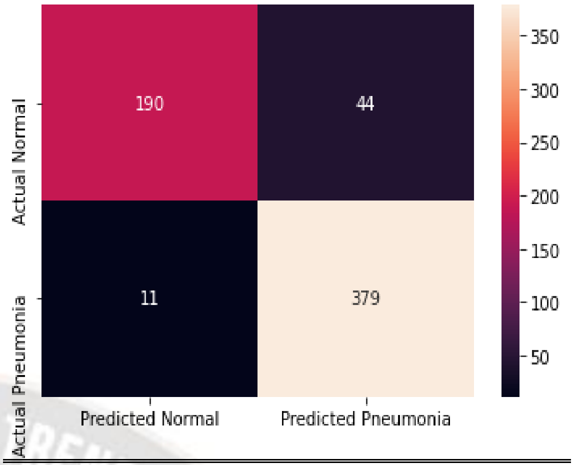

Figure 9. Confusion Matrix

$$Accuracy = \frac{190+379}{190+44+11+379} = 91.18\%$$

$$\text{Precision} = \frac{379}{44+379} = 89.59\%$$

$$\text{Recall} = \frac{379}{44+379} = 97.17\%$$

$$F1-Score = \frac{(2*89.59*97.17)}{89.59+97.17} = 93.22\%$$

VI. CONCLUSIONS

In this research work, we focused on the Big data technology in the medical image classification process on large volumes of data sets. This paper is concentrated mainly on how to apply deep CNN-based methodologies and classification on large-scale X-ray images. We also proposed a workflow with the required steps for medical image classification. CNN methods are the best-in-class approach for artificial learning and training a model traditional method due to their fast-learning selecting capabilities. A very complicated network, on the other hand, is challenging to train and has a tendency to overfit quickly. Due to limited time, A fine-tuned deep neural network trained with unfrozen Conv Layers tends to overgrow in transfer learning, other more powerful CNN models can be used for the training process to be stabilized using efficient methods.

Although they have not been tested, alternatives like resnetv2 and an ensemble of several CNN models might enhance the outcomes. We have used a Spark algorithm that performs feature extraction in this proposed approach. Our proposed model performs better and faster in GPU with even large datasets. The results show that, the model achieved 91.16% of accuracy and 93.22% of F1-score.

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REFERENCES

[1] R. Ashraf et al., "Deep Convolution Neural Network for Big Data Medical Image Classification," in IEEE Access, vol. 8, pp. 105659-105670, 2020, doi: 10.1109/ACCESS.2020.2998808.

[2] Deepika Jaswal, Sowmya.V, K.P.Soman, “Image Classification using Convolutional Neural Networks”, International Journal of Scientific & Engineering Research, Vol.5, Issue 6, June, 2014.

[3] P. N. Kieu, "Applying Multi-CNNs model for detecting abnormal problem on chest x-ray images," in 2018 10th International Conference on Knowledge and Systems Engineering (KSE), 2018.

[4] Y. Bar, I. Diamant, L. Wolf, S. Lieberman, E. Konen and H. Greenspan, "Chest pathology detection using deep learning with non-medical training," 2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI), Brooklyn, NY, USA, 2015, pp. 294-297, doi: 10.1109/ISBI.2015.7163871.

[5] Shah PM, Ullah F, Shah D, Gani A, Maple C, Wang Y, Shahid, Abrar M, Islam SU. "Deep GRU-CNN Model for COVID-19 Detection From Chest X-Rays Data", IEEE Access, 2021 May 5;10:35094-35105. doi: 10.1109/ACCESS.2021.3077592. PMID: 35582498; PMCID: PMC9088790.

[6] Moradi, Mehdi & Madani, Ali & Karargyris, Alexandros & Syeda-Mahmood, Tanveer, "Chest x-ray generation and data augmentation for cardiovascular abnormality classification", 2018, 57. 10.1117/12.2293971.

[7] Lawrence, Tom & Zhang, Li & Lim, Chee & Phillips, Emma-Jane, "Particle Swarm Optimization for Automatically Evolving Convolutional Neural Networks for Image Classification", 2021, IEEE Access, 9. 14369-14386. 10.1109/ACCESS.2021.3052489.

[8] H. Sharma and J. S. Jain, "Feature Extraction and Classification of Chest X-Ray Images Using CNN to Detect Pneumonia," IEEE, pp. 67-73, 2020.

[9] N. N. Zahrani and H. Ramdane , "Comparison Study of Deep-Learning Architectures for Classification of Thoracic Pathology," International Conference on Information and Communication Systems (ICICS), pp. 190-200, 2022.

[10] Y. Yang and Francesco , "Explainable Deep Learning Models on the Diagnosis of Pneumonia," IEEE/ACM Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE), pp. 130-140, 2021.

[11] Trisha Nag and Saurabh , "Detection of Pneumonia using Chest X-Ray Images and Convolutional Neural Network," International Conference on Reliability, Infocom Technologies and Optimization, pp. 5-9, 2021.

[12] Liu Liu, Cong Li, “Comparative study of deep learning models on the images of biopsy specimens for diagnosis of lung cancer treatment”, Journal of Radiation Research and Applied Sciences, Volume 16, Issue 2, 2023, ISSN 1687-8507, https://doi.org/10.1016/j.jrras.2023.100555.

[13] S. Varela-Santos and P. Melin, “Classification of X-Ray Images for Pneumonia Detection Using Texture Features and Neural Networks”, In Studies in Computational Intelligence, edited by A.S. Sdhu, Springer Nature, Mexico, vol.862 pp.237-253, 2020.

[14] T. Tuncer, F.Ozyurt, S.Dogan, and A.Subasi “A novel Covid-19 and pneumonia classification method based on Ftransform,” Chemometrics and Intelligent Laboratory Systems, Elsevier journal, vol.210,15 March 2021.

[15] P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, T. Duan, D. Ding, A. Bagul, C. Langlotz, K. Shpanskaya, M. P. Lungren, and A. Y. Ng, “CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning," 2017, arXiv:1711.05225. [Online]. Available: http://arxiv.org/abs/1711.05225

[16] Josphineleela, R. ., Sundararajan, V. ., K., M. ., Maruthi Varaprasad, A. ., Kumar Yadavalli, P. ., & Praveenadevi, D. . (2023). Ai Based Structural Equation Modelling to Classify the Students’ Performance in Higher Education Institutions. International Journal of Intelligent Systems and Applications in Engineering, 11(4s), 203–212. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2647

[17] N. Nasrullah, J. Sang, M. S. Alam, M. Mateen, B. Cai, and H. Hu, ``Automated lung nodule detection and classi_cation using deep learning combined with multiple strategies," Sensors, vol. 19, no. 17, p. 3722, Aug. 2019.

[18] S. I. Cho, S. Sun, J.-H. Mun, C. Kim, S. Y. Kim, S. Cho, S. W. Youn, H. C. Kim, and J. H. Chung, “Dermatologist-level classification of malignant lip diseases using a deep convolutional neural network,” Brit. J. Dermatol., vol. 182, no. 6, pp. 1388_1394, Jun. 2020.

[19] L. Qu, C. Wu, and L. Zou, “3D dense separated convolution module for volumetric medical image analysis,” Appl. Sci., vol. 10, no. 2, p. 485, Jan. 2020.

[20] J. Son, J. Y. Shin, H. D. Kim, K.-H. Jung, K. H. Park, and S. J. Park, “Development and validation of deep learning models for screening multiple abnormal findings in retinal fundus images," Ophthalmology, vol. 127, no. 1, pp. 85_94, Jan. 2020.

[21] Khatri, R. Jain, H. Vashista, N. Mittal, P. Ranjan, and R. Janardhanan, “Pneumonia identi_cation in chest X-ray images using emd,” in Trends in Communication, Cloud, and Big Data. New York, NY, USA: Springer, 2020, pp. 87_98.

[22] M. Sharma and N. Miglani, “Automated brain tumor segmentation in MRI images using deep learning: Overview, challenges and future,” Deep Learning Techniques for Biomedical and Health Informatics. New York, NY, USA: Springer, 2020, pp. 347_383.

[23] Sherje, D. N. . (2021). Thermal Property Investigation in Nanolubricants via Nano- Scaled Particle Addition. International Journal of New Practices in Management and Engineering, 10(01), 12–15. https://doi.org/10.17762/ijnpme.v10i01.96

[24] G. Lee and H. Fujita, “Deep Learning in Medical Image Analysis: Challenges and Applications”, Springer, vol. 1213. New York, NY, USA, 2020.

[25]] Y. Sun, B. Xue, M. Zhang, and G. G. Yen, “Evolving deep convolutional neural networks for image classification,” IEEE Trans. Evol. Comput., vol. 24, no. 2, pp. 394–407, Apr. 2020.

[26] B. Wang, Y. Sun, B. Xue, and M. Zhang, “A hybrid differential evolution approach to designing deep convolutional neural networks for image classification,” Advances in Artificial

Intelligence, T. Mitrovic, B. Xue, and X. Li, Eds. Cham, Switzerland: Springer, 2018, pp. 237–250.

[27] Omondi, P., Ji-hoon, P., Cohen, D., Silva, C., & Tanaka, A. Deep Learning-Based Object Detection for Autonomous Vehicles. Kuwait Journal of Machine Learning, 1(4). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/149

[28] P. Kinghorn, L. Zhang, and L. Shao, "A hierarchical and regional deep learning architecture for image description generation," Pattern Recognit. Lett., vol. 119, pp. 77–85, Mar. 2019.

[29] Farah Mohammad, Saad AI Ahmadi, Jalal AI Muhtadi, "Blockchain-Based Deep CNN for Brain Tumor Prediction Using MRI Scans", *MDPI Diagnostics* 2023, 13(7), 1229; https://doi.org/10.3390/diagnostics13071229.

[30] Almalki, Y.E.; Ali, M.U.; Kallu, K.D.; Masud, M.; Zafar, A.; Alduraibi, S.K.; Irfan, M.; Basha, M.A.A.; Alshamrani, H.A.; Alduraibi, A.K. , "Isolated Convolutional-Neural-Network-Based Deep-Feature Extraction for Brain Tumor Classification Using Shallow Classifier", Diagnostics 2022, 12, 1793.

[31] Suvita Rani Sharma, Samah Alshathri , Birmohan Singh, Manpreet Kaur, Reham R. Mostafa and Walid El-Shafai, "Hybrid Multilevel Thresholding Image Segmentation Approach for Brain MRI", *Diagnostics 2023*, 13(5), 925; https://doi.org/10.3390/diagnostics13050925.