JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

ENHANCED CLASSIFICATION OF LUNG DISEASE USING RESNET ALGORITHM

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ABSTRACT

In response to the global pandemic, the need for effective identification of COVID-19 and pneumonia has become crucial, especially given the similarity in symptoms between these respiratory conditions and other lung illnesses. Traditional diagnostic challenges prompted the utilization of Chest X-rays as an initial investigative tool for analyzing lung diseases. However, distinguishing between COVID-19 and pneumonia requires advanced image analysis techniques. In this context, the proposed solution employs the ResNet-101 model, a deep residual neural network architecture, implemented in Tensor Flow and Keras. Leveraging the power ofdeep learning, this model is trained on radiographic images to differentiate between COVID-19 and pneumonia, providing a more accurate and efficient diagnostic tool. The developed ResNet-101 model, identified as the best-fit after rigoroustraining and evaluation, is seamlessly integrated into the Django framework. This deployment not only enhances the model's accessibility but also ensures a user-friendly interface for both medical professionals and affected individuals. By incorporating theResNet-101- based classification system into a web application, the flask framework facilitates real-time predictions, aiding in the rapid and accurate identification of COVID-19 and pneumonia cases. This comprehensive approach, combining advanced image analysis with user-friendly deployment, represents a significant stride in improving diagnostic capabilities and addressing the challenges posed by the ongoing pandemic. Our proposed work tackles the diagnostic complexity of distinguishing COVID19 and pneumonia by leveraging Chest X-ray images and employing the ResNet-101 model developed in Tensor Flow and Keras. The integration of this model into the Django framework not only enhances user interaction but also streamlines the deployment of the classification system, offering a valuable tool for accurate and timelydisease identification.

Keywords: Chest X-rays, ResNet-101,

INTRODUCTION

Lung diseases encompass a broad spectrum of disorders affecting the respiratory system, compromising its ability to function optimally. These conditions can be classified into various categories, including chronic obstructive pulmonary disease (COPD), asthma, infections, interstitial lung diseases, and lung cancer, each with unique characteristics and implications for respiratory health [1]. Chronic obstructive pulmonary disease (COPD) is a progressive lung disease characterized by persistent respiratory symptoms and airflow limitation. Mainly caused by long-term exposure to irritants like cigarette smoke, COPD includes conditions such as chronic bronchitis and emphysema. Individuals with COPD often experience breathing difficulties, chronic cough, and increased susceptibility to respiratory infections. Asthma is a chronic inflammatory disorder of the airways, marked by recurrent episodes of wheezing, breathlessness, chest tightness, and coughing.

Triggers, including allergens and irritants, can lead to asthma exacerbations. Management typically involves bronchodilators and antiinflammatory medications to control symptoms and improve airflow. Infections, such as pneumonia and bronchitis, are commonly caused by bacteria, viruses, or fungi. These conditions can lead to inflammation of the lung tissues, resulting in symptoms like fever, cough, and difficulty breathing. Timely diagnosis and appropriate treatment, often involving 2 antibiotics for bacterial infections, are crucial in managing these diseases. Interstitial lung diseases encompass a diverse group of disorders affecting the lung interstitium—the tissue that supports the air sacs. Conditions like idiopathic pulmonary fibrosis (IPF) involve scarring of lung tissue, leading to stiffness and reduced lung function. These diseases often pose challenges in diagnosis and treatment, requiring a multidisciplinary approach for comprehensive care [2]. Lung cancer, a leading cause of cancer-related deaths worldwide, develops when abnormal cells in the lung multiply uncontrollably. Smoking is a major risk factor, but exposure to other carcinogens can also contribute. Early detection through screening and advancements in treatment options, including surgery, chemotherapy, and immunotherapy, have improved outcomes for some individuals with lung cancer.

In summary, lung diseases encompass a range of conditions that impact respiratory function, from chronic and progressive disorders like COPD and asthma to infectious and interstitial lung diseases, as well as the formidable challenge of lung cancer. Early diagnosis, appropriate management, and lifestyle modifications are crucial aspects of mitigating the impact of these diseases on respiratory health [3].

IMAGE PROCESSING : Digital image processing is the use of a digital computer to process digital images through an algorithm. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of multidimensional systems. The generation and development of digital image processing are mainly affected by three factors: first, the development of computers; second, the development of mathematics (especially the creation and improvement of discrete mathematics theory); third, the demand for a wide range of applications in environment, agriculture, military, industry and medical science has increased [1].

PNEUMONIA: Bacterial pneumonia, the most prevalent form of pneumonia, often presents more severe symptoms compared to other types, necessitating prompt medical attention. The onset of symptoms can be gradual or sudden, with fever spiking to potentially dangerous levels, reaching 105 degrees F, accompanied by profuse sweating and a rapid increase in both breathing and pulse rates. A distinctive bluish color may appear on the lips and nailbeds due to insufficient oxygen in the blood, and patients may experience confusion or delirium, reflecting the impact of the infection on mental state. In contrast, viral pneumonia symptoms typically manifest over several days, initially resembling influenza symptoms [6]. Early signs include fever, a dry cough, headache, muscle pain, and weakness. As the infection progresses, symptoms intensify, leading to an increased cough, shortness of breath, and heightened muscle pain. Bluish discoloration of the lips may also occur, indicating decreased oxygen levels in severe cases. These symptoms highlight the challenging nature of viral pneumonia, requiring careful monitoring and medical intervention.

COVID 19 : COVID-19, caused by the novel coronavirus SARS-CoV-2, emerged in late 2019 and swiftly evolved into a global pandemic. The virus primarily spreads through respiratory droplets when an infected person coughs, sneezes, or talks, and it can also spread by touching surfaces contaminated with the virus. The incubation period ranges from 2 to 14 days, during which an individual can be asymptomatic yet contagious, contributing to the rapid spread of the virus. Common symptoms include fever, cough, and difficulty breathing, with a spectrum ranging from mild cases to severe respiratory distress, particularly among older adults and individuals with underlying health conditions [8].

DEEP LEARNING : Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behavior of the human brain— allowing it to “learn” from large amounts of data. While a neural network with a single layer can still make approximate predictions, additional hidden layers can help to optimize and refine for accuracy [4]. In deep learning, a computer model learns to perform classification tasks directly from images, text, or sound. Deep learning models can achieve state-of-the-art accuracy, sometimes exceeding human-level performance. Models are trained by using a large set of labeled data and neural network architectures that contain many layers. It is a field that is based on learning and improving on its own by examining computer algorithms. However, advancements in Big Data analytics have permitted larger, sophisticated neural networks, allowing computers to observe, learn, and react to complex situations faster than humans. Deep learning has aided image classification, language translation, speech recognition. It can be used to solve any pattern recognition problem and without human intervention [8].

NEURAL NETWORKS : Deep learning algorithms attempt to draw similar conclusions as humans would by continually analyzing data with a given logical structure. To achieve this, deep learning uses a multi-layered structure of algorithms called neural networks. The design of the neural network is based on the structure of the human brain. Just as we use our brains to identify patterns and classify different types of information, neural networks can be taught to perform the same tasks on data [6].

TYPES OF DEEP NEURAL NETWORKS : Three following types of deep neural networks are popularly used today: 1. Multi-Layer Perceptrons (MLP) 2.Convolutional Neural Networks (CNN) 3. Recurrent Neural Networks (RNN) MULTI-LAYER PERCEPTRONS(MLP) A multilayer perceptron (MLP) is a class of a feedforward artificial neural network (ANN). MLPs models are the most basic deep neural network, which is composed of a series of fully connected layers. Today, MLP machine learning methods can be used to overcome the requirement of high computing power required by modern deep learning architectures. Each new layer is a set of nonlinear functions of a weighted sum of all outputs (fully connected) from the prior one [8].

CONVOLUTIONAL NEURAL NETWORK (CNN) : A convolutional neural network (CNN, or ConvNet) is another class of deep neural networks. CNNs are most employed in computer vision. Given a series of images or videos from the real world, with the utilization of CNN, the AI system learns to automatically extract the features of these inputs to complete a specific task, e.g., image classification, face authentication, and image semantic segmentation [14]. Different from fully connected layers in MLPs, in CNN models, one or multiple convolution layers extract the simple features from input by executing convolution operations. Each layer is a set of nonlinear functions of weighted sums at different coordinates of spatially nearby subsets of outputs from the prior layer, which allows the weights to be reused [8].

RECURRENT NEURAL NETWORKS : Recurrent neural networks, or RNNs, are a type of artificial neural network that add additional weights to the network to create cycles in the network graph in an effort to maintain an internal state. The promise of adding state to neural networks is that they will be able to explicitly learn and exploit context in sequence prediction problems, such as problems with an order or temporal component [6].

LONG SHORT-TERM MEMORY NETWORKS : With conventional Back-Propagation Through Time (BPTT) or Real Time Recurrent Learning (RTTL), error signals flowing backward in time tend to either explode or vanish. The temporal evolution of the back-propagated error exponentially depends on the size of the weights. Weight explosion may lead to oscillating weights, while in vanishing causes learning to bridge long time lags and takes a prohibitive amount of time, or does not work at all [6]. • LSTM is a novel recurrent network architecture training with an appropriate gradient-based learning algorithm. • LSTM is designed to overcome error backflow problems. It can learn to bridge time intervals in excess of 1000 steps. • This true in presence of noisy, incompressible input sequences, without loss of short time lag capabilities. Error back-flow problems are overcome by an efficient, gradient-based algorithm for an architecture enforcing constant (thus neither exploding nor vanishing) error flow through internal states of special units. These units reduce the effects of the “Input Weight Conflict” and the “Output Weight Conflict.”

RESNET ALGORITHM : After the first CNN-based architecture (AlexNet) that win the ImageNet 2012 competition, Every subsequent winning architecture uses more layers in a deep neural network to reduce the error rate. This works for less number of layers, but when we increase the number of layers, there is a common problem in deep learning associated with that called the Vanishing/Exploding gradient. This causes the gradient to become 0 or too large. Thus when we increases number of layers, the training and test error rate also increases.

In the above plot, they have observed that a 56- layer CNN gives more error rate on both training and testing dataset than a 20-layer CNN architecture. After analyzing more on error rate the authors were able to reach conclusion that it is caused by vanishing/exploding gradient. ResNet, which was proposed in 2015 by researchers at Microsoft Research introduced a new architecture called Residual Network [6]. Residual Network: In order to solve the problem of the vanishing/exploding gradient, this architecture introduced the concept called Residual Blocks. In this network, they have used a technique called skip connections. The skip connection connects activations of a layer to further layers by skipping some layers in between. This forms a residual block. Resnets are made by stacking these residual blocks together [8]. The approach behind this network is instead of layers learning the underlying mapping, we allow the network to fit the residual mapping. So, instead of say $H(x)$, initial mapping, let the network fit, $F(x) := H(x) – x$ which gives $H(x) := F(x) + x$. 5

IMPLEMENTATION: In the midst of the global Covid-19 pandemic, the pressing necessity for rapid and accurate 6 respiratory disease diagnosis has become increasingly evident. The virus's potential to induce pneumonia and present symptoms that overlap with various other conditions, such as fatigue, dry cough, and fever, underscores the critical importance of precise diagnostic tools. This study strategically taps into the impressive capabilities of deep learning algorithms, leveraging their prowess in detecting and classifying a spectrum of lung diseases. By emphasizing the role of these algorithms in streamlining diagnostic procedures, the research aims to provide medical practitioners with efficient tools for timely and accurate identification of respiratory illnesses.

The proposed deep learning (DL) architecture is a focal point of this study, specifically designed for the classification of various respiratory conditions, including Pneumonia, Lung Cancer, Tuberculosis (TB), Lung Opacity, and Covid-19. The dataset employed is extensive, encompassing a substantial number of chest X-ray (CXR) images for each disease category, spanning from Covid-19 cases to normal instances. Rigorous preprocessing measures, including resizing, normalization, and random splitting, are undertaken to ensure the readiness of the images for DL requirements. Notably, the study integrates the powerful ResNet-101 neural network architecture for prediction, highlighting the fusion of advanced DL algorithms and state-of-the-art architectures to enhance accuracy and establish a robust framework for respiratory disease classification. This innovative integration serves as a pioneering approach to meeting the imperative need for efficient and accurate respiratory disease diagnosis during the challenging landscape of the Covid-19 pandemic. By combining the strengths of DL algorithms and ResNet-101, the research strives to contribute significantly to the development of advanced diagnostic tools that can aid in the global efforts to combat respiratory diseases effectively.

DISPLAYING THE DATSET : To display both training and validation images, you can utilize Python libraries like Matplotlib or OpenCV. This process involves accessing the image directories for both datasets, selecting a representative subset of images, and then visualizing them in a grid layout. This visualization offers a qualitative assessment of the data and ensures that preprocessing steps Fig 3.2 Bar chart for train and test validation have been applied correctly. It also provides insights into the characteristics and diversity of the dataset. Typically, you would iterate through the image files in each directory, loading them using a library like OpenCV, and then displaying them using Matplotlib's `imshow()` function. Each image can be accompanied by its filename or other relevant information to aid in analysis. By visualizing both training and validation images, you can gain a better understanding of the dataset's composition and quality, which is crucial for effective model training and evaluation.

MODEL CREATION USING THE RESNET 101: Model creation using ResNet-101 involves constructing a deep convolutional neural network architecture based on the ResNet framework. This process typically begins by importing the ResNet-101 architecture from a deep learning library such as TensorFlow or PyTorch. The ResNet-101 model consists of multiple layers of convolutional, pooling, and fully connected layers, organized into residual blocks. These residual blocks include skip connections that allow for the effective training of very deep networks by mitigating the vanishing gradient problem. After importing the ResNet-101 architecture, the next step is to customize the model for the specific classification task at hand. This may involve adjusting parameters such as input shape, number of output classes, and fine-tuning layers to adapt the model to the target dataset. Additionally, transfer learning techniques can be applied by initializing the model with pretrained weights on a large dataset like ImageNet, which helps accelerate convergence and improve performance on the target task.

EPOCHE RUNNING: Achieving an accuracy of 96% indicates that the ResNet-101 model has demonstrated a high level of proficiency in correctly classifying instances within the dataset. This metric signifies that 96% of the instances in the dataset were accurately classified by the model, reflecting its ability to distinguish between different classes with a high degree of accuracy. In practical terms, this level of accuracy suggests that the model is effective in its classification task and can provide reliable predictions for new, unseen data with a high level of confidence. However, while accuracy is a valuable metric for evaluating model performance, it's essential to consider other metrics such as precision, recall, and F1 score, especially in scenarios with imbalanced datasets or when certain classes are more critical than others. Additionally, it's crucial to assess the model's performance on a separate validation or test dataset to ensure its generalization capabilities and guard against overfitting to the training data. Overall, achieving a 96% accuracy is indicative of a well-performing model, but further analysis and validation are necessary to fully understand its effectiveness in real-world applications.

RESULT AND DISCUSSION

The graph depicting the accuracy prediction provides a visual representation of how the accuracy of the ResNet-101 model evolves over time during the training process. Typically, this graph illustrates the performance of the model on the training dataset across multiple epochs or iterations. As training progresses, the accuracy of the model is monitored and recorded after each epoch, allowing for the visualization of trends and patterns in the model's learning process. In an ideal scenario, the accuracy graph exhibits a steady increase over epochs, indicating that the model is continuously improving its performance and learning to make more accurate predictions. However, it's not uncommon to observe fluctuations or plateaus in the accuracy curve, which may be indicative of factors such as model convergence, overfitting, or underfitting.

Analysing the accuracy prediction graph enables researchers and practitioners to assess the effectiveness of the training process and identify potential issues that may need to be addressed, such as adjusting learning rates, introducing regularization techniques, or modifying the model architecture. Additionally, comparing the accuracy prediction graph with other evaluation metrics such as loss curves can provide further insights into the model's behaviour and performance.

TRAINING AND VALIDATION LOSS: The training and validation loss are key metrics used to evaluate the performance of a machine learning model, such as the ResNet-101, during the training process. The training loss represents the error between the model's predictions and the actual labels of the training data. As the model iteratively learns from the training data through backpropagation and parameter updates, the training loss ideally decreases over time. This reduction indicates that the model is effectively minimizing its error and improving its ability to make accurate predictions on the training dataset. On the other hand, the validation loss is computed using a separate dataset called the validation set, which consists of examples that the model has not been trained on. This allows for an assessment of the model's performance on unseen data, serving as a proxy for its generalization ability. Similar to the training loss, the validation loss ideally decreases during training, indicating that the model is not only memorizing the training data but also learning to generalize well to new, unseen examples. Analysing the trends of the training and validation loss curves provides valuable insights into the model's learning dynamics. A decreasing training loss coupled with a decreasing validation loss suggests that the model is learning effectively without overfitting to the training data.

CONFUSION MATRIX: The provided matrix shows heatmap visualization of a confusion matrix, a valuable tool for evaluating the performance of a classification model like ResNet-101. The confusion matrix compares the model's predicted labels with the true labels from the dataset, displaying the frequency of correct and incorrect predictions for each class. The heatmap visualization enhances the interpretation of the confusion matrix by colorcoding the cells based on the proportion of correct predictions, with annotations providing precise values for clarity. The colormap chosen ensures clear visualization of the data, while the addition of a title and axis labels improves the plot's readability. Overall, the heatmap visualization offers insights into the model's performance across different classes, aiding in the identification of classification errors and areas for refinement.

CONCLUSION

In conclusion, the proposed system represents a significant stride forward in the realm of respiratory disease diagnosis, particularly during the unprecedented challenges posed by the global Covid-19 pandemic. The pressing need for accurate and rapid identification of respiratory illnesses is met through the strategic application of advanced deep learning algorithms, emphasizing their efficiency in streamlining diagnostic processes. The proposed deep learning architecture, designed for multi-class classification of diverse respiratory conditions, including Pneumonia, Lung Cancer, Tuberculosis (TB), Lung Opacity, and Covid-19, stands as a testament to the versatility and adaptability of the system. The extensive dataset, comprising a diverse range of chest X-ray (CXR) images meticulously pre-processed to meet deep learning requirements, underscores the system's commitment to comprehensive model training. 9 The integration of the powerful ResNet-101 neural network architecture for prediction elevates the system's accuracy, showcasing a commitment to leveraging state-of-the-art technologies. This innovative fusion of advanced deep learning algorithms and cuttingedge architectures establishes a robust framework that not only meets the immediate challenges posed by the Covid-19 pandemic but also contributes significantly to the broader landscape of respiratory disease diagnostics. In essence, the proposed system emerges as a pioneering solution, embodying a commitment to technological advancement and its potential to enhance global efforts in combating respiratory diseases. Through the integration of advanced algorithms and architectures, the system aspires to revolutionize respiratory disease diagnosis, offering an efficient, accurate, and timely approach that aligns with the evolving demands of healthcare in the face of complex and dynamic public health challenges**.**

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