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REVOLUTIONIZING HEALTHCARE: AN IN-DEPTH ANALYSIS OF DEEP LEARNING MODELS

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Abstract

The healthcare sector is characterized by a vast amount of information and holds significant potential for improvement through the integration of state-of-the-art technologies. Deep learning models have been regarded as being particularly ideal since they can efficiently handle and analyze enormous amounts of data, allowing them to attain the highest possible level of accuracy. This study aims to conduct a comprehensive analysis of various deep learning models by comparing their performance on different datasets. Additionally, it will focus on the practical application of the VGG-16 and AlexNet models specifically on the ChestX-ray14 dataset. The evaluation of the accuracy of numerous deep-learning models is conducted to assess the efficacy and performance of such models. Among the array of models available, the Genetic Deep Learning Convolutional Neural Network (GDCNN), DenseNet-201, and Convolutional Neural Network (CNN) have emerged as top contenders, showcasing superior performance and robustness. The GDCNN achieved an accuracy of 98.84 percent, and DenseNet-201 exhibited an accuracy of 97.2 percent. Notably, the CNN outperformed the other models with an accuracy of 99.39 percent. The incorporation of a larger dataset, the addition of more convolutional layers to the CNN, and image segmentation techniques may enhance the overall performance and accuracy levels.

Keywords: Deep Learning Predictive Models, Diseases, Lung Cancer, Pneumonia, Tuberculosis.

I. Introduction

The conventional healthcare industry encounters numerous challenges, encompassing the effective handling of vast volumes of data, safeguarding patient privacy, ensuring accurate diagnostic testing, and enhancing early disease detection capabilities. The implementation of information and communications technology (ICT) in healthcare settings, specifically artificial intelligence (AI), has emerged as a highly promising approach to address various challenges in this domain. Deep learning, a prominent subfield within the realm of artificial intelligence, necessitates the capability to effectively handle a wide array of data to produce accurate and dependable predictions about various illnesses. In the present study, the deep learning models have been applied to various datasets to produce accurate projections. The adoption of deep learning techniques for lung cancer detection is on the rise, reflecting an increasingly prevalent trend in medical research and diagnostics. The NIH-14 dataset, the RSNA dataset, the SEER dataset, and the Kaggle collection from multiple authors have emerged as prominent choices for evaluating and benchmarking various f in the field. Convolutional neural networks (CNNs), often abbreviated as CNNs, along with the Deep Survival learning model, are recognized as the forefront models in the field, demonstrating exceptional performance and advancement. The models achieved an accuracy of 74% when utilizing the SEER database, 94.32% when employing the Kaggle dataset, and an impressive 99.39% when leveraging the RSNA database in conjunction with other datasets [I, XXXV, XXXVI,].

The development of new tuberculosis detection techniques is ongoing. Out of all the easily accessible datasets, those from the “National Library of Medicine in China and the United States”, NIH, RSNA, and Kaggle's repository from various authors are the most widely used. The most often utilized models among the tested models are CNN, ANN, Multiclass CNN, and Deep learning models. Whereas the validation accuracy of Multiclass CNN with various datasets is 99.93%, the test accuracy is 99.01Based on data from the National Library of Medicine in China and the United States, the CNN and ANN models achieve impressive accuracies of 99.2% and 99.8%, respectively [XIV, XII, XXIX, XXXVI].

Several studies have been conducted in the area of applying deep learning to the diagnosis of pneumonia. Out of all the available datasets, those from the NIH, Kaggle's Pulmonary Mask database, Radiopaedia, Mendeley, and GitHub repositories from various authors are the most widely used. The most often utilized models among the tested models are CNN, DNN, and deep learning models. The accuracy of the CNN model is 96 percent across many datasets, whereas the accuracy of the DNN model is almost 100 percent [II, XVIII, XXV, XXXVI].

This paper is broadly divided into six sections, apart from the other subsections: Bibliometric analysis; deep learning models for lung cancer; pneumonia; tuberculosis; comparative analysis and performance evaluation; and design and implementation of deep learning models. One of the most important activities to assess the potential of a research field and direction is the Bibliometric analysis. Here, databases from PubMed, Web of Science, and Scopus are used to conduct a Bibliometric analysis covering the years 2012 to 2022. It has been discovered that deep learning algorithms are the most popular and best at processing vast volumes of data.

II. Existing Predictive Deep Learning Techniques for disease detection: Bibliometric Analysis

The amount of data keeps growing as a result of digitization and advancements in computational methods. The deep learning algorithms are ideal for the processing of large amounts of data. The latest comprehensive review encompasses studies conducted between 2012 and 2022, providing a thorough analysis of a substantial portion of research conducted in this domain. The bibliometric analysis is divided into two sections: the author analysis and the keyword analysis.

To appreciate, evaluate, and interpret the value of the research done in this area, Bibliometric analysis of over 4308 recent publications retrieved from the PubMed, Web of Science, and Scopus databases using the search term "deep learning in illness prediction" was conducted. Based on authors and keywords, a Bibliometric map has been made using VOSviewer [III]. Bibliometric analysis proves invaluable for structuring investigations into specific topics. With digitization and the integration of artificial intelligence in healthcare, 2022 anticipates a significant surge in research studies, reflecting the expanding scope and impact of these advancements. The tool has discovered a total of 23225 authors, and 286 of those authors satisfy the threshold. According to the analysis, the following writers “You, Zhu-hong", "Shen, Dihggang", and "wang, lei" have contributed 23, 20, and 19 papers respectively. Figure 1 illustrates the visual network portraying various terms utilized in the published literature to elucidate the application of deep learning models in disease prediction.

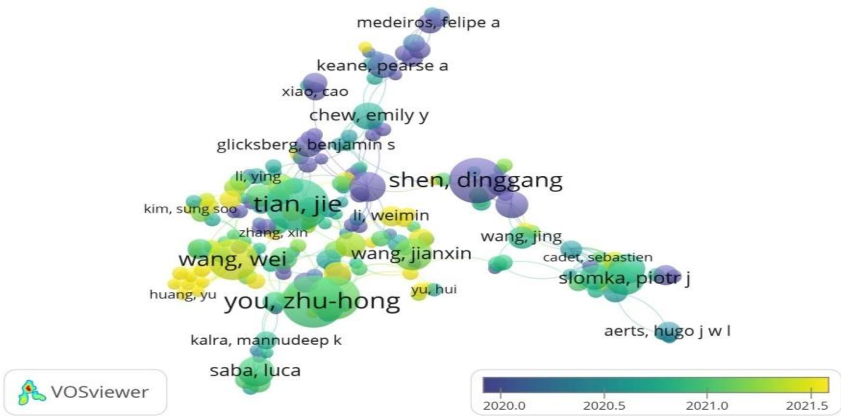

Fig. 1. The visual network of authors who have written articles about utilizing deep learning to forecast diseases from 2002-2022.

To capture the diverse array of keywords used by researchers in papers published between 2002 and 2022, a minimum occurrence threshold of 5 for each keyword was set. Out of 9754 keywords examined, 936 met this threshold requirement, offering a robust representation of the terminology used in the field. Figures 2 depict the visual network of several authors who have written on the prediction of diseases using deep learning.

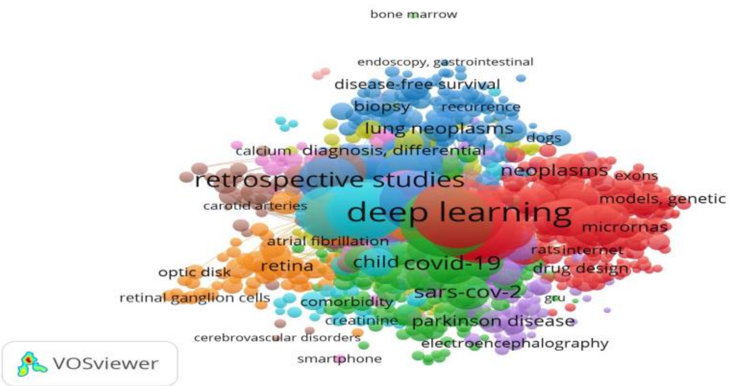

Fig. 2. The application of deep learning techniques in disease prediction is described in published literature using a visual network of keywords from 2002-2022.

Figure 3 provides a graphical representation of keyword occurrence in research papers. Among 9754 keywords analyzed, the top 10 keywords, including "humans," "deep learning," "machine learning," "neural networks," "computer," "artificial intelligence," "algorithms," "female," "male," and "middle-aged," occur with frequencies of 2637, 2538, 1161, 878, 878, 779, 643, 612, 555, and 424, respectively.

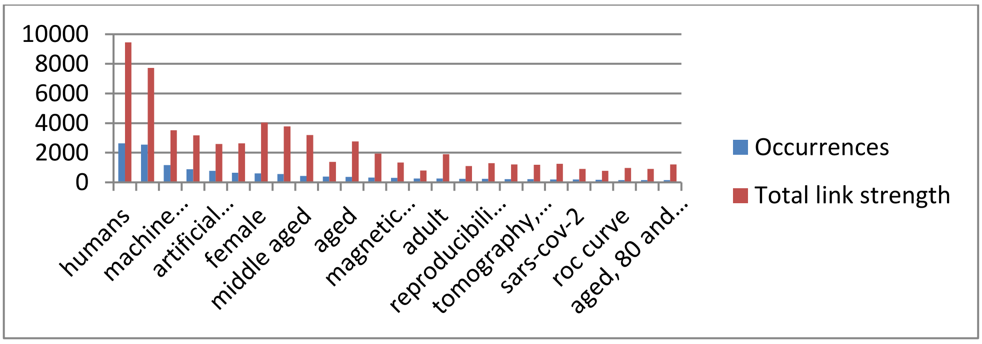

Fig. 3. Representation of occurrences and total link strength of various keywords used in the papers published during 2002-2022.

Advanced methodologies and techniques utilizing deep learning for lung cancer detection

The prevalence of deep learning methods is increasing in the realm of lung cancer detection. The most popular datasets out of all those that are accessible are RSNA, SEER, and the Kaggle repository from various authors. CNN and the Deep Survival learning model are the most well-liked models among the different evaluated algorithms. With the SEER database, these models' accuracy is 74%; with the Kaggle's dataset, it is 94.32%; and with the RSNA and other datasets, it is 99.39% as depicted in Table 1. By taking into account the drawbacks and applying their remedies, the models may be further enhanced. Accurate and future-ready picture segmentation, data imbalance, and clinical trials must all be incorporated into the model to make it more resilient; doing so will further boost the model's dependability and accuracy.

Deep learning models and Techniques for the Detection of Tuberculosis

New methods for the detection of tuberculosis are being developed as mentioned in table 2. “The National Library of Medicine from China and the United States”, NIH, RSNA, and Kaggle's repository from diverse authors are the most popular datasets out of all those that are readily available. Among the models examined, CNN, Multiclass CNN, ANN, and various Deep learning models emerge as the most frequently utilized options. While the test accuracy of Multiclass CNN is 99.01 percent, the validation accuracy is 99.93 percent with several datasets. The accuracy of the CNN and ANN models using data from the National Libraries of Medicine in China and the United States is 99.2 percent and 99.8 percent, respectively. Deep feature extraction, colour picture segmentation, multilayer introduction, and clinical trials may all be used to further develop the models, which will boost their accuracy and dependability.

Table 1. Review result of deep learning techniques for detection of lung cancer.

References	Deep learning Techniques	Data sets	Accuracy (%)	Research gaps
[XXXV]	DenseNet-201	Kaggle’s dataset, Marsh Metadata, datasets from other authors	97.49	Image segmentation and deployment of the model need to be addressed.
[XXXVI]	CNN	Github, SIRM, TICA, Radiopaedia, Mendeley, Repository, Kaggle’s Repository, LC dataset, and RSNA database	99.39	The clinical trial missing and supporting inputs are very less.
[I]	The deep survival learning model	SEER database	74	The interpretation of deep learning models for real-life applications may be studied in the future.

Deep learning models and Techniques for the Detection of Pneumonia

Numerous studies have been done in the field of using deep learning to the prediction of pneumonia illness as shown in table 3. The most popular datasets out of all those that are accessible include those from the NIH, Kaggle's Pulmonary Mask database, Radiopaedia, Mendeley, and GitHub repositories from various authors. CNN, DNN, and deep learning models are the most widely used models among the tested models. With several datasets, the accuracy of the CNN model is 96%, whereas the accuracy of the DNN model is almost 100%. Consideration of data augmentation, the incorporation of multilayer, and clinical trials may all be used to further improve the models, increasing their accuracy and dependability.

Table 2: Review results of Deep Learning techniques for the Detection of Tuberculosis.

References	Deep learning Techniques	Data sets	Accuracy (%)	Research gaps
[XXXVI]	Multiclass CNN	Github, SIRM, TICA, Radiopaedia, Mendeley, NIH, Kaggle LC, and RSNA	Training accuracy: 99.01, Validation accuracy: 98.93	The clinical trial missing and supporting inputs are very less.
[XIV]	CNN, ANN	Data set-1: "National Library of Medicine with Guangdong Medical College China and Shenzhen No. 3, People's Hospital" Data set-2: "National Library of Medicine of the United States, The National Institute of Allergy and Infectious Diseases, The Republic of Belarus, and the NIAID website."	99.2 with CNN 99.8 with ANN	It must incorporate deep learning feature extraction and Vectorization to improve efficiency.
[XXIX]	CNN, PCA, Inception V3, MobileNet V1	RSNA	For Inception V3: without processing (Validation accuracy: 83, Test accuracy:74.6	Rigorous preprocessing is required to improve model performance. Colored image segmentation can improve performance.
[XII]	GoogleNet (Inception), ResNet Architecture	NIH clinical center	84.3	Additional Convolution layers need to be used to capture the low-level details in order to achieve better results.

Table 3: Review results of Deep Learning Techniques for the Detection of Pneumonia.

References	Deep learning Techniques	Data sets	Accuracy (%)	Research gaps
[XXXVI]	CNN	Data set-1: Kaggle's chest X-ray. Data set-2: Guangzhou Women and Children's Medical Centre, Guangzhou	96	Model generalization has not been studied. The clinical trial missing and supporting inputs are very less.
[XVIII]	CNN	Github, SIRM, TICA, Radiopaedia, Mendeley, NIH, Kaggle's, LC, and RSNA	99.39	The clinical trial missing and supporting inputs are very less.
[XXV]	Deep Learning-based Neural Network	National Institutes of Health (NIH)	100	The size of the middle convolutional layers and first layer smaller needs improvement. Need to reduce parameters in the network.
[II]	Improved BoxENet	Kaggle X-Rays datasets, BelPnem	95.4 with X-ray segmentation and 97.4 without segmentation	The clinical trial missing and supporting inputs are very less.

III. Comparative analysis and performance evaluation

In Table 4, the comparative analysis of illness prediction utilizing deep learning approaches is shown. VGG16 (For image categorization, the Visual Geometry Group suggested a 16-layer CNN architecture. It is regarded as one of the most acute models for computer vision), Densenet121 (Dense Convolutional Network is a deep learning architecture with 121 layers, including 117 convolution layers, three transition layers, and one classification layer), Resnet18 (The 18-layer, pre-trained Resnet18 deep learning model includes eleven million training parameters), SqueezeNet (SqueezeNet is an 18-layer, pre-trained deep learning network.), and GDCNN(The Genetic Deep Learning CNN architecture has been accurately pre-trained on 5000 images) are determined to be the best deep learning models among those that the authors applied.

Table 4: Comparison of Deep Learning models for Respiratory Disease.

References	Disease	Data sets	Deep learning Model	Accuracy (%)
[XXVI]	Lung cancer	com/shervinmin/DeepCovid/tree/mas	Densenet 121, VGG16, ResNet18 , Squeeze Net, GDCNN	Densenet121= 91.91, VGG16= 88.05 , ResNet18= 93.35 , SqueezeNet = 96.60, GDCNN = 98.84
[XXXV]	Tuberculosis, Pneumonia	1. URL for the dataset: "https://www.kaggle.com/datasets/tawsifurrahman/tuberculosis-tb-chest-xray-dataset" 2.1. URL for the dataset:https://www.kaggle.com/datasets/jtiptj/chest-xray-pneumoniaCOVID-19tuberculosis. 3.1. URL for the dataset **https://www.kaggle.com/datasets/prashant268/**	Darknet19, GoogleNet, MobileNetV2, DenseNet-201	Darknet19 = 96.23, GoogleNet = 93, MobileNetV2= 95.69, DenseNet-201= ~ 97.2
[II]	2 classes (Pneumonia , Normal)	BelPnem	Improved BoxENet	95.4 with segmentation 97.4 without segmentation

The graphical comparison was created to demonstrate the viability of several deep-learning respiratory disease models. Between accuracy and deep learning models, a graphical study has been conducted. Figure 4 displays a graphical comparison of deep-learning models with tuberculosis and pneumonia. The maximum accuracy, 97.2 percent, is demonstrated by DenseNet-201.

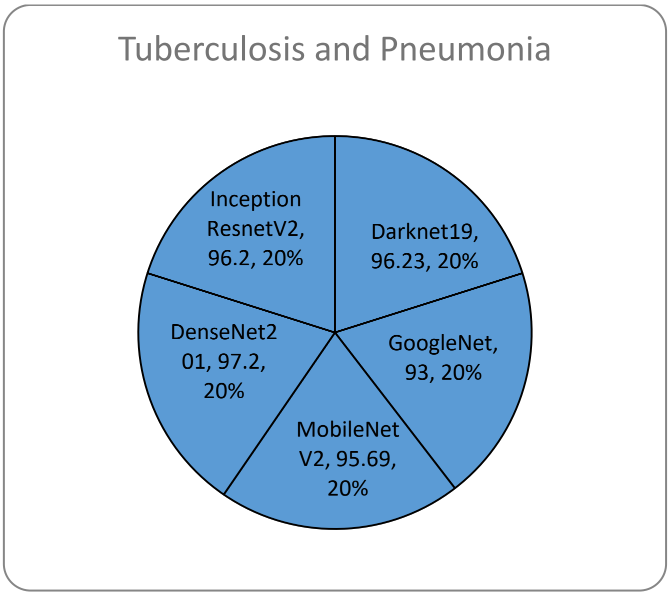

Fig. 4. The graphical comparison of deep learning models and tuberculosis and pneumonia.

The graphical comparison between deep learning models and lung cancer is shown in Figure 5. The convolutional neural network is considered the top-performing model, achieving an impressive accuracy of 99.39 percent.

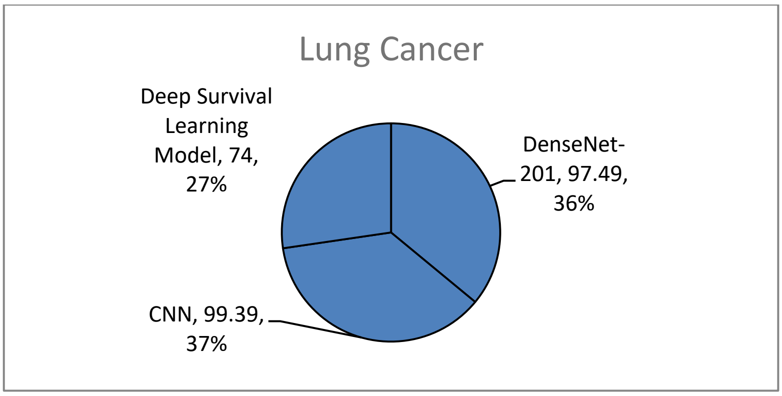

Fig. 5. The graphical comparison of deep learning models and Lung Cancer.

IV. Design and Implementation of deep Learning Predictive Models in Healthcare

The current deep-learning models suited to the healthcare industry have been analyzed in this work. It has been observed that VGG16, Densenet121, Resnet18, SqueezeNet, and GDCNN to be the best deep learning models, although the accuracy of Desnenet121, Resnet18, SqueezeNet, and GDCNN is between 90% and 98 percent, which indicates an overfitting of the model. In this work, it has been observed that VGG16 is the best option because of its moderate to high accuracy. As a result, it has been decided to incorporate VGG16 as one of the models. Since comparison has to be done with the same setup with a new model, thus AlexNet has been chosen as another model to be implemented. The two deep learning models VGG-16 and AlexNet have been deployed on the Chest X-ray 14 dataset to find and compare the accuracy with existing models on various data sets.

Dataset Description: ChestX-ray14

The ChestX-ray14 dataset [IX] was created by the NIH and contains 30,805 unique medical images from 1992 to 2015. The dataset, which contains fourteen distinct disease labels, aims to use the data for a variety of disease-focused projects. The PNG pictures, Metadata, and Bounding boxes constitute the three categories that make up the dataset's content. 112,120 frontal view chest X-ray images with a resolution of 1024 by 1024 are included in the dataset. The "Data Entry 2017.csv" file is used to hold the information about the dataset and has the following information as shown in Table 5.

Table 5. Review Results of Deep Learning techniques for the detection of Pneumonia.

S.No.	Dataset features
1.	Image Index
2.	Patient ID
3.	Patient Age
4.	Patient Gender
5.	Follow-up number
6.	View Location
7.	Original Image Size
8.	Finding Labels

AlexNet Architecture

Convolutional Neural Network Architecture known as AlexNet won the 2012 LSVRC 9 (Large Scale Visual Recognition Challenge) competition. As a part of the LSVRC competition, teams of researchers are pitted against one another to see whose algorithm performs the best on a massive dataset of labeled images (called ImageNet) [XIX]. This had a profound effect on the way teams approached the final product in AlexNet, there are eight weighted layers [XXX]. Out of eight layers, five are convolutional layers and the remaining three are linked layers.

To activate ReLu in each layer, except for the final one, a softmax distribution is applied over the thousand class labels. The dropout is performed in the first two layers.

Max-pooling layers have been added after the first, second, and fifth layers of CNN to achieve the best results possible [XXXI]. The subsequent layer's all-piece maps are associated with the third layer's bits. The neurons in the past layer are all associated with the neurons in the layers above them in the pecking order of availability.

VGG-16

The model, also recognized as OxfordNet, pays tribute to the Visual Geometry Group at the University of Oxford. Comprising 16 layers, each carrying unique weights denoted by the number 16, it embodies a sophisticated architecture. This just includes the Convolution and pooling layers. The size of the 3x3 Kernel for convolution, and the max pooling as 2x2 has been used. It is fine-tuned using ImageNet data and has a 92.7% accuracy rate. VGG 19 is a different variation of it with a total weight of 19 layers. For all layers, the kernel and pool are both 3x3. The VGG 16 model takes input images with dimensions of 224x224x3 pixels. Subsequently, it features two convolution layers, each sized 224x224x64, succeeded by a pooling layer that reduces the image dimensions to 112x112x64 in both height and width [XXXII]. Each conv128 layer has a 112x112x128 size, and the pooling layer again reduces the image's height and width to 56 X 56 X 128-pixel dimensions. A pooling layer reduces the image's size to 28x28x256 after three conv256 layers, each measuring 56x56x256. A pooling layer reduces the image size to 14 X 14 X 512 = three conv512 layers with each 28 X 28 X 512 pixels.

A pooling layer with 7x7x521 nodes follows, followed by three conv512 layers with 14x14x521 nodes each, before two thick or completely associated layers with 4090 hubs each. At long last, there is a thick or result layer with 1000 hubs of the size, which characterizes pictures into 1000 different picture nets.

Model Architecture on ChestX-ray14Dataset

The deep learning models AlexNet [XXX] and VGG-16[XXXII] have been deployed on NIH ChestX-ray14datasets to find and compare the accuracy with existing models on various data sets. This multilayer model consists of one input, one output, and three hidden layers, with 17,305 total Trainable Parameters in the Chest X-ray14 dataset as shown in Figure 6.

Layer (type)	Output Shape	Param #	Param #
dense_5 (Dense)	(None, 50)	9400	9400
dense_6 (Dense)	(None, 50)	2550	2550
dense_7 (Dense)	(None, 50)	2550	2550
dense_8 (Dense)	(None, 50)	2550	2550
dense_9 (Dense)	(None, 5)	255	102

```
Total params: 17,305
Trainable params: 17,305
Non-trainable params: 0
```

```
Total params: 17,152
Trainable params: 17,152
Non-trainable params: 0
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Fig. 6. Model Architecture based on Chest X-ray14 datasets.

V. Results and Discussions

To assess the validation accuracy and validation loss of the models in comparison to the accuracy of the existing deep learning model examined in this research, AlexNet and VGG-16 have been deployed on Chest X-ray14 datasets. The accuracy and loss produced by the AlexNet model when applied to the Chest X-ray14 dataset are 0.972 and 0.0211, respectively, while the total validation accuracy and loss are determined to be 91.75 percent and 9.63 percent, respectively. When the VGG-16 model is applied to the Chest X-ray14 dataset, the accuracy and loss come out to 0.83327 and 0.0291, respectively, while the total validation accuracy and loss come out to 79.8 and 4.28 percent, respectively. In Table 6, the results of an analysis comparing AlexNet and VGG-16 findings are displayed.

Table 6. Comparison of Model Result.

ChestX-ray14 DATA SET				
MODEL	LOSS	ACCURACY	VALIDATION LOSS	VALIDATION ACCURACY
ALEXNET	0.0211	0.972	0.0963	0.9175
VGG-16	0.0291	0.83327	0.0428	0.798

When the AlexNet deep learning model is applied, the ChestX-ray14 dataset exhibits an improvement in validation accuracy as well as overall accuracy up to epoch 17. Up until epoch 17, loss and validation loss decrease as the epoch advances. The accuracy and total validation accuracy are respectively 91.75 and 97.20 percent, while the loss and validation loss are separately 2.11% and 9.63%.

On the other hand, the VGG-16 model displays an improvement in validation accuracy and overall accuracy up to epoch 17 when applied to the Chest X-ray14 dataset. Loss and validation loss decreases with increasing epoch up to epoch 17. The accuracy and total validation accuracy are respectively 83.32% and 79.80%, while the loss and validation loss are respectively 2.91% and 4.28%.

VI. Review Challenges

Deep learning models are especially well-suited for visual datasets in terms of accuracy for the prediction and diagnosis of various illnesses. There is no doubt that AI has the potential to dramatically change the healthcare sector. The healthcare industry has a variety of unresolved issues, but researchers are working to implement AI algorithms. Figure 7 provides a visual summary of existing Deep Learning models for improved comprehension through visualization. Lung cancer, pneumonia, and tuberculosis existing deep learning models are each diagrammatically depicted along with information about their model name, accuracy, and features.

The second part of the figure focuses on the review challenges and major problems, with privacy issues, model-based issues, data-related issues, and trans-disciplinary research issues being the four major issues [XXVII, XL, IV, VII, V, XXXIII, XVI, XIII]. Data integrity, authorization, and authentication, as well as data and device anonymity, are the main privacy concerns. The interoperability of models, model-driven ML difficulties, model evaluation, and model validation are the main areas of concern in mode-based challenges. When it comes to data-related problems, availability, consistency, redundancy, and legitimacy of the data are the main areas of concern [X, XI, XV, XVII]. Translation and adapting research so that it can be generalized are the key hurdles in the case of trans-disciplinary topics. A significant difficulty is the integration of AI in trans-disciplinary decision-making processes [VIII, XXXIII]. Despite numerous advances in this field, finding lung cancer is a difficult undertaking. The authors examined several well-liked solutions to these problems [XXXIV]. The authors went over the major problems surrounding clinical decision-making for local and distant patients. To solve the significant gaps in current healthcare support systems, they proposed an Internet of Things and Clinical Decision Support System [XXII]. The authors highlight the ethical problems with AI. Any data or model that uses AI must be applied following their suggested ethical framework [XXXIX]. The accuracy of the model was improved by building an ensemble model, which the authors analyzed and compared with other deep learning models [XXII]. The authors assessed the dataset from Kaggle's library and then applied a machine learning model to it to determine how well it predicted the coronavirus-related disease [XXXVII]. The author faced many difficulties when putting up a model with training and testing accuracy up to 98.4 and 94.94, respectively, to diagnose lung disease [XXXVI]. To diagnose Retinopathy of Prematurity early with 88.23% accuracy, the authors suggested a Deep Convolutional Neural Network and image processing technique [XXXVIII]. The authors examined the current security precautions and suggested a course of action for safeguarding healthcare systems in the future [VI]. The problems and potential connected to machine learning and sensing approaches in the field of cardiovascular disease risk factors were evaluated by the author [XX]. In the domain of lung cancer, the author analyzed potential directions, issues, and several computer-aided drug design techniques [XXVIII].

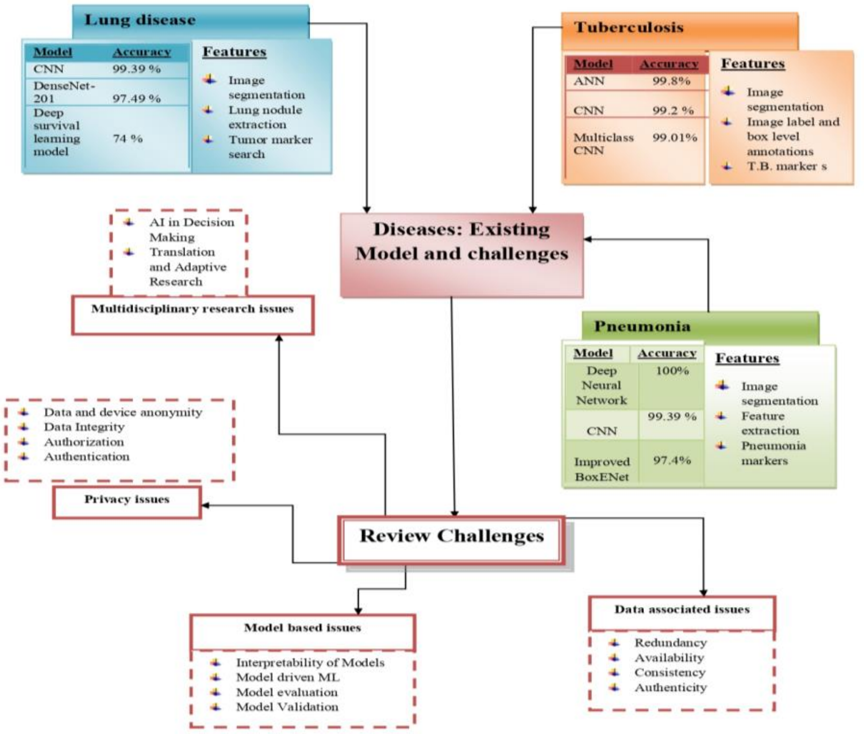

Fig. 7. Review challenges in Predictive Models in Healthcare

VII. Conclusion and Future Scope

The accuracy of multiple deep-learning models is evaluated for the prediction of diseases using deep learning, such as lung cancer, TB, and pneumonia. To demonstrate the effectiveness of several deep-learning respiratory disease models, a visual comparison was created. With accuracy rates of 98.84 percent, 97.2 percent, and 99.39 percent, respectively, GDCNN, DenseNet-201, and convolutional neural networks are shown to be the most useful deep learning models for TB, pneumonia, and lung cancer. AlexNet and VGG-16 have been implemented on ChestX-ray14 datasets. When used with the ChestX-ray14 dataset, the AlexNet model produced accuracy and loss of 0.972 and 0.0211, respectively. The accuracy and loss of the entire validation were found to be 91.75 percent and 9.63 percent, respectively. The accuracy and loss for the ChestX-ray14 dataset using the VGG-16 model are 0.83327 and 0.0291, respectively, while the accuracy and loss for the entire validation are 79.8 and 4.28 percent, respectively.

The inclusion of the bigger dataset could result in improved accuracy. To better capture the low-level information, extra convolutional layers may be added. X-ray image segmentation may be used to produce pseudo-colored images before feeding them into the CNN input layers for better results.

Conflict of Interest:

There was no relevant conflict of interest regarding this paper.

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