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A Data Driven Machine Learning Approach for Predictive Analytics in Healthcare Domain

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Abstract: - Machine Learning and Deep Learning are transforming the healthcare domain so as to aid medical practitioners with effective analytical tools which can find pattern in copious amounts of data and augment the diagnosis and potential health risks. While the use of statistical techniques may be shrouded with skepticism for the healthcare sector, its inevitability came into light recently with the Covid-19 pandemic wherein the number of cases saw an exponential growth stressing the healthcare infrastructure. The sudden outbreak of such a global medical emergency stressed upon the need to develop intelligent computational models which can analyze medical datasets and render results pertaining to the onset or existence of a disease, potential cases and hotspots in the future. Such systems would offload the existing medical infrastructure and also give medical practitioners valuable inputs as a strong second opinion. Such systems would also render primary screening in remote location where necessary medical facilities are unavailable. Additionally, controlling and arresting potential pandemic like situations, by identifying potential hotspots or estimating future number of cases would also allow government agencies. This paper presets a data driven approach for classifying medical images, as well as a regression model for forecasting future cases. A comparative analysis with benchmark models in the domain of research clearly indicates that the proposed model outperform exiting research in terms of classification and forecasting accuracy.

.***Keywords:*** Machine Learning, Deep Learning, Healthcare, Biomedical Datasets, Feature Extraction, Regression, Classification Accuracy.

1. INTRODUCTION

Research in the domain of leveraging machine learning and deep learning models have garnered a lot of attention off late, especially during and after the Covid-19 pandemic. This was primarily due to the following reasons [1]:

1. Exponential increase in the number of cases over time.
2. High mortality rates.
3. Insufficient medical infrastructure (Such as CT and MRI Scan Centers)
4. Limited medical and paramedical staff to cater to the increasing number of patients.
5. Substantial economic losses due to travel and work related restrictions.

This lead to the need for expediting development of machine learning based models for the healthcare domain [2]. The health care sector is one of the most crucial domains where technology is making transformative impacts. Among the cutting-edge technologies, machine learning (ML) and deep learning (DL) have emerged as game changers, revolutionizing how medical data is analyzed, diseases are detected, and treatments are personalized. With the growing complexity of health challenges, these technologies are increasingly becoming indispensable for advancing patient care, medical research, and operational efficiency [3]. The situation became non-trivial and needed immediate attention with the onset of unprecedented pandemic such as the Covid-19. Other cases such as the onset of Monkeypox also stressed on the need for efficient and accurate data based models to accurately classify and predict future cases.

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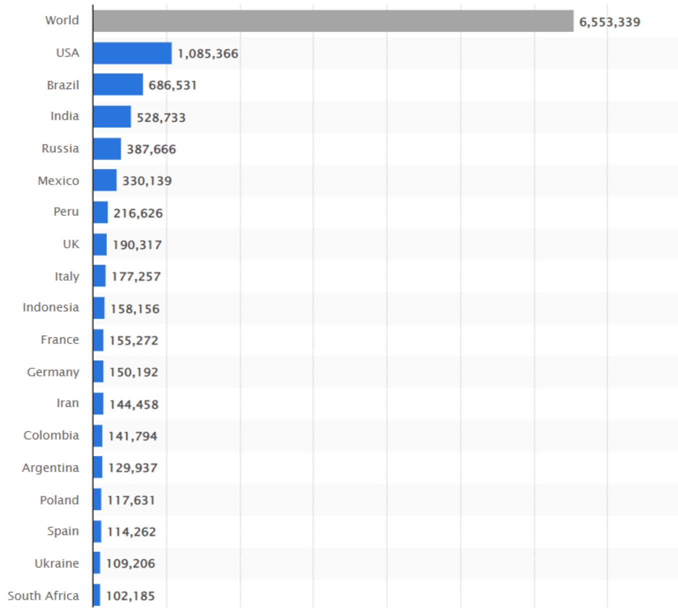

Fig.1 Number of deaths due to Covid-19 Worldwide as of 2022

(https://www.researchgate.net/publication/350155002_Emerging_Public_Health_Paradigms_in_Relation_to_COVID-19_A_review)

Figure 1 depicts the Number of deaths due to Covid-19 Worldwide as of 2022. A similar outbreak of the monkeypox was seen in the USA, with a lesser magnitude of effect.

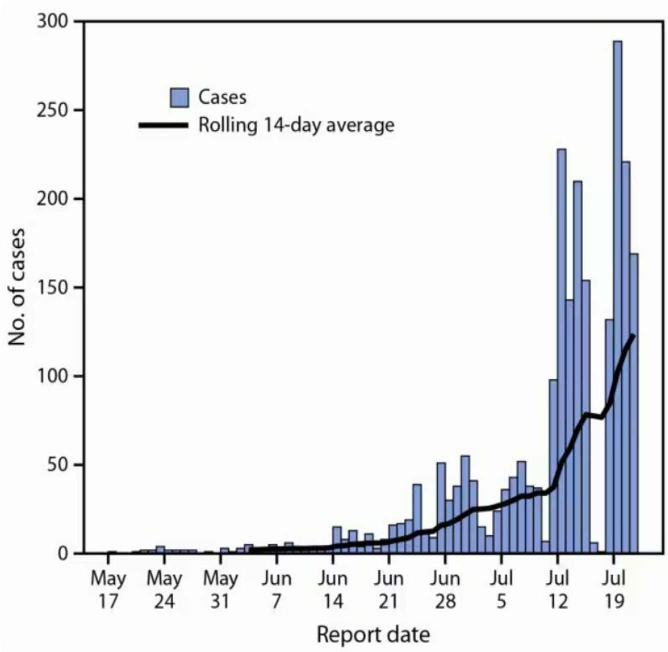

Fig.2 Rise in Monkeypox cases reported in the United States, during 17–July 22, 2022

(Source: CDC, https://www.cdc.gov/mmwr/volumes/71/wr/mm7132e3.htm)

Figure 2 depicts the rise in monkeypox cases worldwide. Thus, conditions such as the Covid-19 and monkey pox clearly indicated that drastic measures need to be taken for early detection and prevention of such epidemic and pandemic like cases, which made it mandatory to used machine learning and deep learning models for the purpose [4]. Machine learning, a subset of artificial intelligence, involves training algorithms to recognize patterns and make data-driven predictions. In health care, ML is extensively used for tasks such as diagnosing diseases, predicting patient outcomes, and optimizing hospital operations. For instance, ML algorithms can analyze electronic health records (EHRs) to identify early warning signs of diseases, enabling timely interventions [6]. Additionally, ML models help reduce administrative burdens by automating routine processes like patient triage and resource allocation, improving the overall efficiency of health care systems. ML and DL are central to the development of personalized medicine, which aims to tailor treatments to individual patients based on their unique genetic, clinical, and lifestyle profiles [7]. Machine learning models analyze vast datasets, including genomic information, to predict how patients will respond to specific treatments. Deep learning further accelerates drug discovery by simulating molecular interactions, reducing the time and cost of bringing new therapies to market. This personalized approach ensures better treatment outcomes and minimizes adverse effects, ultimately improving the quality of patient care [8].

2. APPLICATIONS OF MACHINE LEARNING AND DEEP LEARNING BIOMEDICAL CLASSIFICAITON AND REGRESION PROBLEMS

There are several applications of machine learning and deep learning models for classification as well as prediction problems related to biomedical datasets for the healthcare sector. Biomedical research and health care are domains that generate massive amounts of complex data daily. Machine learning (ML) and deep learning (DL) have become indispensable tools for tackling biomedical classification and regression problems [9]. These methods enable researchers and clinicians to analyze and interpret data efficiently, supporting accurate decision-making in diagnosis, treatment, and prognosis. The versatility of ML and DL algorithms allows them to address a variety of tasks, ranging from disease classification to predicting patient outcomes, making them transformative technologies in biomedical science [10].

2.1 Classification Problems:

Classification problems involve categorizing data into predefined classes. In biomedical contexts, ML and DL algorithms are widely used for disease diagnosis and detection. For example, ML models can classify medical images to distinguish between normal and abnormal tissues, such as identifying lung cancer in chest X-rays or classifying benign versus malignant tumors in histopathology images. Similarly, DL techniques like convolutional neural networks (CNNs) excel in analyzing high-dimensional data, such as genomic sequences, to identify biomarkers for genetic disorders [11]. These tools also facilitate rapid screening of diseases like diabetes, Alzheimer's, and cardiovascular conditions, significantly improving early diagnosis and treatment outcomes [12].

2.2 Regression Problems:

Regression problems involve predicting continuous outcomes based on input variables. In biomedical research, ML and DL algorithms are extensively used for tasks such as predicting disease progression, patient survival rates, and drug response [13]. For instance, regression models analyze patient data to forecast blood sugar levels in diabetic patients or estimate the risk of complications following surgery. Deep learning techniques, including recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, are particularly effective for modeling time-series data, such as monitoring heart rate variability or tracking the progression of neurodegenerative diseases. These predictions enable clinicians to make informed decisions and optimize patient care plans [14].

2.3 Predictive Potential Health Risks:

Machine learning algorithms excel in processing structured data, such as demographic information, lab results, and electronic health records (EHRs). Techniques like decision trees, support vector machines (SVMs), and random forests are commonly used to predict risks [15]. For instance, ML models can predict the likelihood of developing type 2 diabetes based on factors such as age, BMI, and family history. Similarly, predictive models assess the risk of heart disease by analyzing cholesterol levels, blood pressure, and lifestyle habits. These tools not only improve accuracy but also enable personalized risk assessments tailored to individual patients [16].

ML and DL are also transforming public health by enabling large-scale risk predictions. For example, predictive models analyze population data to forecast the spread of infectious diseases, such as COVID-19 or influenza, guiding public health interventions [17]. Similarly, these technologies help identify at-risk groups for chronic diseases, enabling targeted health campaigns and resource allocation.

Environmental factors, such as air quality and water contamination, can also be integrated into predictive models to assess risks for respiratory or gastrointestinal illnesses [18].

2.4 Potential Non-Trivial Challenges:

Despite their potential, the application of ML and DL in health risk prediction faces challenges. Ensuring the quality and diversity of data is crucial for building reliable models [18]. Bias in training data can lead to inaccurate predictions, particularly for underrepresented populations. Additionally, ensuring model interpretability and transparency is essential for gaining trust in clinical settings [20]. Privacy concerns must also be addressed, as health risk prediction relies on sensitive personal data. Overcoming these challenges requires collaboration between health care professionals, data scientists, and policymakers [21].

The quality and diversity of datasets also influence the accuracy of ML and DL models, requiring efforts to eliminate biases and ensure inclusivity. Moreover, integrating these technologies into clinical workflows demands substantial investment in infrastructure and workforce training. Overcoming these hurdles is critical for unlocking the full potential of ML and DL in health care [22].

3. METHODOLOGY

This section presents the methodology for proposed work, which is categorized in two sections:

1. Classification Analysis
2. Regression Analysis

This paper presents feature extraction followed by classification though a probabilistic deep neural network model based in image dataset. However, prior to image feature extraction, denoising through the discrete wavelet transform has been employed [23]. Image denoising is a critical task in image processing and computer vision, as it aims to remove unwanted noise from images while preserving essential features such as edges and textures [24].

3.1 Data Pre-Processing

Among various denoising techniques, the discrete wavelet transform (DWT) has emerged as an effective and versatile method. DWT leverages the multi-resolution analysis of images, breaking them down into frequency components for noise suppression. This approach is widely used in medical imaging, satellite imaging, and other applications requiring high-quality image restoration [25].

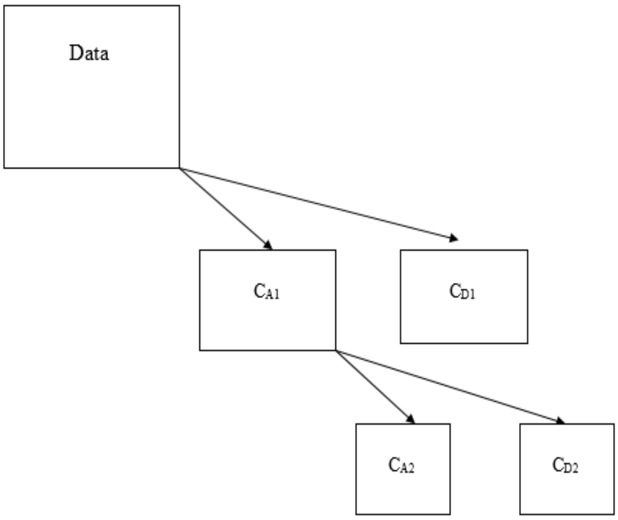

Fig.3 The DWT filtration process

Figure 3 depicts the filtration process using the DWT. The discrete wavelet transform is a mathematical tool that decomposes an image into different frequency bands, separating the high-frequency components (representing edges and noise) from the low-frequency components (representing the main structure). By analyzing the image in both spatial and frequency domains, DWT provides a detailed representation of the image. This decomposition is achieved through successive filtering and down-sampling operations, creating sub-bands such as approximation, horizontal, vertical, and diagonal details [26].

While several filtration mechanisms such the mean filter, median filter, discrete cosine transform (DCT) etc. have been explored, one of the most effective data filtration techniques which filters data in the transform domain happens to be the discrete wavelet transform (DWT). The DWT of any function $z(x)$ is computed as [27]:

$$\boldsymbol{Z(x, \Theta_0^n, i\Theta_0^n) = \delta_0^{n\frac{-1}{2}} \sum_i z(x) K^*} \left[\frac{n - i\Theta_0^n}{\Theta_0^n}\right] \quad \textbf{(1)}$$

Here,

$z(x)$ = time series vector

K^* = wavelet kernel

Z = data in the transform domain or DWT domain

Θ_0^n = scaling operation

$i\Theta_0^n$ = shifting operations

δ_0^n = dilation constant of the transform

3.2 Feature Extraction

Feature extraction is a crucial step in image classification, as it transforms raw image data into meaningful representations that can be used by classification algorithms. One widely used technique for texture analysis is the Gray Level Co-occurrence Matrix (GLCM), which captures spatial relationships between pixel intensities in an image. GLCM-based features provide a robust way to characterize texture and are commonly used in medical imaging, remote sensing, and industrial inspection applications. GLCM features are particularly effective in capturing texture, making them ideal for classifying images based on their structural properties [28]. For example, in medical imaging, GLCM features help differentiate between normal and abnormal tissues, such as classifying benign and malignant tumors. In remote sensing, they are used to distinguish between different land cover types, such as forests, water bodies, and urban areas. By providing quantitative measures of texture, GLCM features enhance the accuracy and reliability of classification algorithms [29].

The image based features extracted are:

a) Mean or average value:

$$\boldsymbol{Mean\ or\ \mu = \frac{1}{N} \sum_i^N f_i X_i} \quad \textbf{(2)}$$

b) Standard Deviation:

$$\boldsymbol{sd = \sqrt{\frac{1}{N} \sum_i^N (X_i - \mu)^2}} \quad \textbf{(3)}$$

c) Energy which is also considered as the secondary moment:

$$\boldsymbol{Energy = \sum_{i,j}^n \left|A_{i,j}\right|^2} \quad \textbf{(4)}$$

d) Variance is the squared value of s.d. given by:

$$\boldsymbol{variance = sd^2} \quad \textbf{(5)}$$

e) Contrast which is the deviation among the mean and differential change in illuminance:

$$\boldsymbol{Contrast} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{mn}}\sum_{\boldsymbol{i,j}}^{\boldsymbol{m,n}}[\boldsymbol{X}(\boldsymbol{i,j}) - \boldsymbol{\mu}(\boldsymbol{i,j})]^{\mathbf{2}}} \quad \textbf{(6)}$$

f) Entropy which is the statistical average information content defined as:

$$\boldsymbol{E} = -\boldsymbol{P}(\boldsymbol{I}_{\boldsymbol{x,y}})\boldsymbol{log}_{\mathbf{2}}\boldsymbol{I}_{\boldsymbol{x,y}} \quad \textbf{(7)}$$

g) Homogeneity which is the similarity among the pixel value distribution:

$$\boldsymbol{H} = \sum_{\boldsymbol{i,j}}^{\boldsymbol{m,n}}\frac{\boldsymbol{P}_{\boldsymbol{I,J}}}{\mathbf{1}-[\boldsymbol{i}-\boldsymbol{j}]^{\mathbf{2}}} \quad \textbf{(8)}$$

h) Correlation which is the similarity overlap among pixel values:

$$\boldsymbol{Correlation}_{\boldsymbol{i,j}} = \sum_{\boldsymbol{i,j}}^{\boldsymbol{m,n}}\frac{(\boldsymbol{i}-\boldsymbol{u}_{\boldsymbol{x}})(\boldsymbol{j}-\boldsymbol{\mu}_{\boldsymbol{j}})\boldsymbol{P}_{\boldsymbol{j}_{\boldsymbol{x,y}}}}{\boldsymbol{sd}_{\boldsymbol{x}}\boldsymbol{sd}_{\boldsymbol{y}}} \quad \textbf{(9)}$$

i) Root Mean Square Value which is defined as the squared root of the squared mean of values in the random distribution defined as:

$$\boldsymbol{rms} = \sqrt{\frac{\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}}\boldsymbol{X}_{\boldsymbol{i}}}{\boldsymbol{n}}} \quad \textbf{(10)}$$

The normalizing factor for the gray covariance matrix (GLCM) is defined as:

$$\boldsymbol{N} = \frac{\boldsymbol{X}_{\boldsymbol{i,j}}}{\sum_{\boldsymbol{i}=\mathbf{0}}^{\boldsymbol{m}-\mathbf{1}}\sum_{\boldsymbol{j}=\mathbf{0}}^{\boldsymbol{n}-\mathbf{1}}{*}\boldsymbol{X}_{\boldsymbol{i,j}}} \quad \textbf{(11)}$$

Here,

X_i denotes random variable X

f denotes the frequency of occurrence

$I_{x,y}$ denotes an image which is a function of spatial co-ordinates (x, y)

m, n denote the pixels along x and y axes

$mean$ denotes the average illuminance of the image

A denotes the amplitude

N denotes levels of normalized GLCM matrix

$p_{i,j}$ denotes the normalized GLCM matrix

P denotes probability

GLCM-based feature extraction offers several benefits for image classification. It is computationally efficient and easy to implement, making it suitable for a wide range of applications. Additionally, GLCM features are robust to minor variations in image brightness and contrast, ensuring consistent performance across different imaging conditions. Furthermore, their ability to capture both fine and coarse texture details makes them versatile for various classification tasks [30].

3.3 Feature Optimization

It is necessary to avoid chances of overfitting and vanishing gradients in medical datasets due to highly redundant values. Principal component analysis (PCA) has been employed in this approach. The idea of the PCA or ICA is maximizing the variance among the samples of the random variable while simultaneously reducing the correlation, mathematically represented as [31]:

$$\boldsymbol{Maximize}\ (\boldsymbol{V}(\boldsymbol{l}^{\boldsymbol{T}}\boldsymbol{f})) \quad \textbf{(12)}$$

Here,

V denotes variance.

$\boldsymbol{l^T f}$ denotes the l dimensional feature vector.

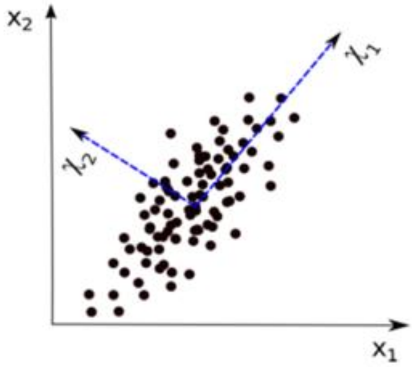

Fig.4 Visualization of PCA

Figure 5 depicts the visualization of the PCA/ICA wherein two orthogonal vectors X_1 and X_2 are to be found so as to maximize the variance of the dataset.

PCA helps eliminate redundancy in data by identifying and removing correlated features. In many datasets, certain features are highly correlated and do not contribute unique information. By combining these features into a single principal component, PCA minimizes redundancy and provides a more compact representation of the data. This not only improves interpretability but also ensures that models trained on PCA-transformed data focus on the most relevant information, enhancing performance. As the number of dimensions increases, the performance of many machine learning algorithms deteriorates due to the "curse of dimensionality." High-dimensional spaces lead to sparse data distributions, making it difficult to identify meaningful patterns. PCA addresses this issue by reducing the number of dimensions while preserving the essential structure of the data. This helps models generalize better and prevents overfitting, especially when working with small datasets [32].

PCA often improves the performance of machine learning models by removing noise and irrelevant features. By focusing on the most informative components, PCA reduces the impact of irrelevant or redundant variables that can introduce noise and degrade model accuracy. This leads to better feature selection and enables models to learn more effectively from the data, improving predictive performance and robustness [34].

3.4 The Deep Neural Network Model

This paper presents a probabilistic neural network model for classifying medical image datasets a well as a regression model for forecasting future cases. The neural networks are arguably the most sought after models presently owing to their variable, non-linear and dense structure [35]. A neural network is just a group of these neurons connected in some way. Depending on its topology, the neural network may execute tasks ranging from basic to complicated. It is planned to identify a mathematical model after examining the neural network's underlying biological model. The mathematical model of the neural network can be represented as:

$$\boldsymbol{Y} = \boldsymbol{f}\left(\sum_{i=1}^{n} \boldsymbol{XiWi} \; + \; \boldsymbol{b}\right) \tag{13}$$

Where,

Xi shows the signals that arrive from various paths,

Wi denotes the weight corresponding to the various paths.

b is the bias.

f stands for the activation function.

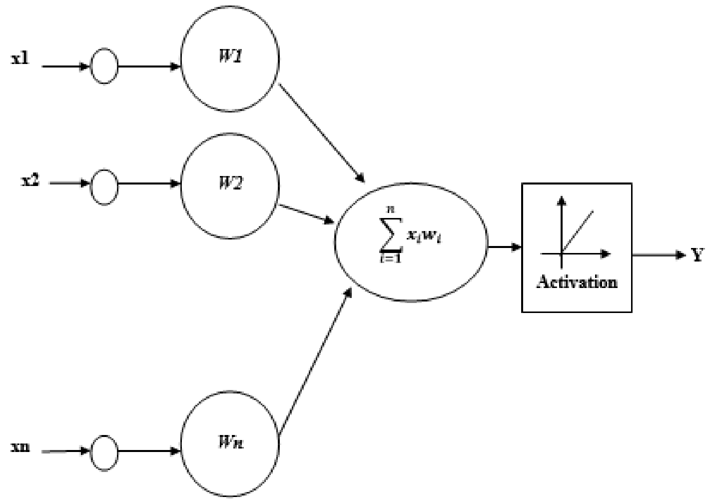

Fig.5 Mathematical Model of Neural Network.

Figure 5 depicts the typical mathematical counterpart of the neural network model. The essence of the model happens to be the fact that the data streams $(x_1, \ldots\ldots x_n)$ are fed in parallel which in turn create experiences or weight $(w_1, \ldots\ldots w_n)$ as the data streams serve as the input to the model. As the iterations keep on increasing, an objective function is typically minimized to get the best mapping of the inputs and the target variable. The conceptual structure of the neural network model is depicted in figure 6.

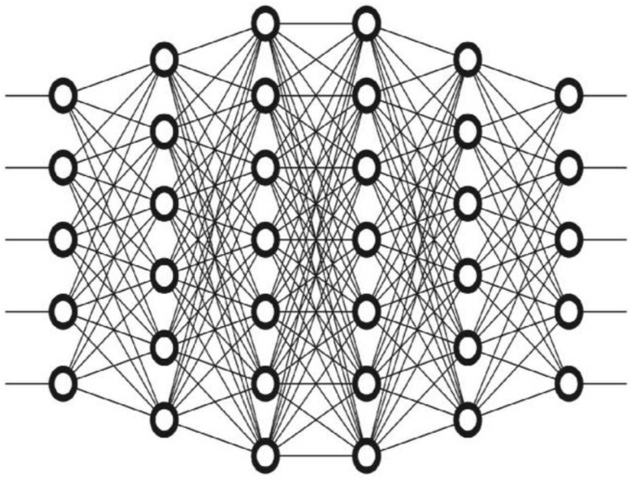

Fig.6 Deep Neural Network Model

The essence of this model is the stacked hidden layer structure which is able to compute low level as well as high level features at the outer and inner layers of the network. This paper employs the regularization based Bayesian Optimization algorithm to train the deep neural network model. Bayesian regularization is a statistical approach that applies Bayes' theorem to the optimization of deep learning models. Unlike traditional regularization methods, which penalize large weights to prevent overfitting, Bayesian regularization treats model parameters as random variables with prior distributions. By combining these priors with the likelihood of the data, the approach computes a posterior distribution that balances model complexity with data fit. This probabilistic framework provides a more nuanced approach to regularization, allowing the model to adapt dynamically to the data [36].

As the data features may have overlapping values, hence a probabilistic Bayes Classifier has been proposed. As features do not possess a particular decision boundary (fixed), hence a probabilistic approach happens to be more effective which can be done employing the Deep Bayes Net whose classification depends on the following relation [37]:

$$\boldsymbol{P}\left(\frac{\boldsymbol{X}}{\boldsymbol{X_i},\boldsymbol{k_1},\boldsymbol{k_2},\boldsymbol{M}}\right) = \frac{\boldsymbol{P}\left(\frac{\boldsymbol{X_i}}{\boldsymbol{X},\boldsymbol{k_2},\boldsymbol{M}}\right)\boldsymbol{P}\left(\frac{\boldsymbol{X_i}}{\boldsymbol{k_1},\boldsymbol{M}}\right)}{\boldsymbol{P}\left(\frac{\boldsymbol{X}}{\boldsymbol{k_1},\boldsymbol{k_2},\boldsymbol{M}}\right)} \quad \textbf{(14)}$$

Here,

Prepresents probability.

$X_i$represents weights and bias vectors (combined).

Xrepresents the data to be used for the purpose of training.

Mrepresents data units (neurons) in network.

k_1 and $k_2$represents the term responsible for penalty based regularization.

$\rho = \frac{k_1}{k_2}$ is often considered the regularization factor which is acted upon the objective function (J) to me optimized based on the training dataset, and renders the regularized cost function:

$$\boldsymbol{F(w) = \mu w^T w + v[\frac{1}{n}\sum_{i=1}^{n}(p_i - a_i)^2]} \quad \textbf{(15)}$$

If $(\pi \ll v)$:errors in training are typically rendered low.

else if $(\pi \geq v)$:errors are typically rendered high needing a weight reduction or Penalty.

Algorithm

Start

{

Step.1 Obtain annotated dataset.

Step.2 Divide the data into a ratio of 70:30 as training and testing data samples.

Step.3 Define maximum number of iterations and error tolerance as:

$\boldsymbol{Max\ Itr = 1000\ and\ e_{tolerance} = 10^{-6}}$

Step.4: Define number of DWT levels $(\boldsymbol{n})$

Step.5: Employ DWT based filtration as:

$\boldsymbol{for\ i = 1{:}n}$

Retain $(\boldsymbol{C_A})$ **while discarding** $(\boldsymbol{C_D})$

end .for.

Step.6: Apply PCA.

Step.7: Design a neural network with multiple hidden layers.

Step.9 Initialize training with random weights.

Step.10 $\boldsymbol{for\ i = 1{:}\ Max.Iterations}$

Train models with training data and updated weights based on the back propagation rule as:

$\boldsymbol{w_{k+1} = w_k - \left[J_k J_k^T + \mu' I\right]^{-1} J_k^T e_k}$

end for

Step.11: if (Cost Function J stabilizes over multiple iterations)

Truncate Training

else if (iterations==max. iterations defined)

Truncate Training

else

{

Apply data and update $(\boldsymbol{w}, \boldsymbol{b})$

Feedback (e)

}

Step.12 Calculate error% and Accuracy

}

Stop

3.5 Classification Metrics

The performance metrics computed are [38]:

Accuracy (Ac): It is mathematically defined as:

$$\boldsymbol{Ac = \frac{TP+TN}{TP+TN+FP+FN}} \quad \textbf{(16)}$$

Recall: It is mathematically defined as:

$$\boldsymbol{Recall = \frac{TP}{TP+FN}} \quad \textbf{(17)}$$

Precision: It is mathematically defined as:

$$\boldsymbol{Precisiosn = \frac{TP}{TP+FP}} \quad \textbf{(18)}$$

F-Measure: It is mathematically defined as:

$$\boldsymbol{F - Measure = \frac{2.Precision.Recall}{Precision+Recall}} \quad \textbf{(19)}$$

The Mean Absolute Percentage Error (MAPE) is computed as:

$$\boldsymbol{MAPE = \frac{1}{N}\left(\sum_{i=1}^{N}\frac{|P_i - A_i|}{A_i}\right) * 100} \quad \textbf{(20)}$$

Here,

N is the number of testing samples

P is predicted review score

A is actual review score

Accuracy is computed as:

$$\boldsymbol{Accuracy = 100 - MAPE\%} \quad \textbf{(21)}$$

The experimental results are presented next.

4. EXPERIMENTAL RESULTS

The experiments have been performed in a PC with 16GB of RAM and Intel i5 Processor and dedicated NVIDIA GTX Graphics. The simulation tool used is MATLAB. The functions of the NNET and Deep Learning toolboxes have been used. The Covid-19 dataset from Kaggle has been used for the purpose.

The training and Testing split has been kept at 70:30. The experimental results for denoising, feature extraction and classification have been presented next:

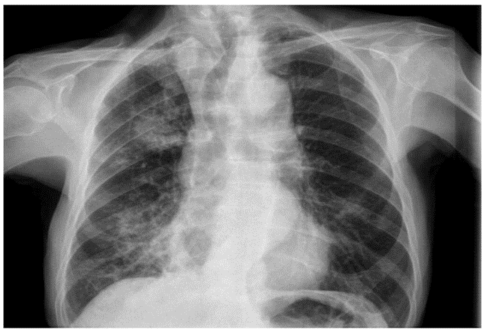

Fig.7 Test Image

Figure 7 depicts the test image loaded to MATLAB.

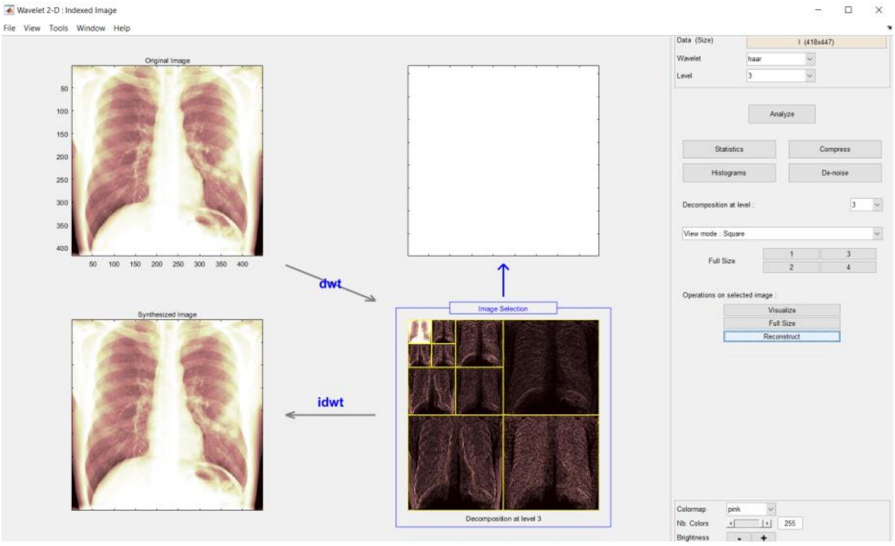

Fig.8 Image Denoising using DWT

Figure 8 depicts the image denoising using the DWT where the(C_A) values are to be retained while discarding (C_D) values. The next step is the application of PCA and feature extraction.

Table 1. Extracted Features for test image

Features	Values
F_1	0.430681818181818
F_2	0.0837345693095003
F_3	0.701628357438016
F_4	0.910946969696970
F_5	0.00673805612638039
F_6	0.106415989706705
F_7	3.41369018153386
F_8	0.106600358177805
F_9	0.0112116087571718

F_{10}	0.925661212229239
F_{11}	8.04957673628005
F_{12}	0.825465508561976

Table 1 depicts the features computed for the test image.

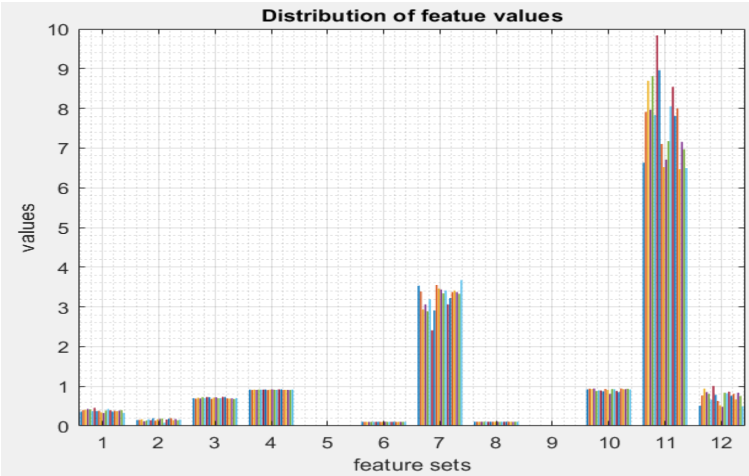

Fig.9 Distribution of feature vectors

Figure 9 depicts the distribution of feature vectors. The next process is training the deep neural network, with annotated features. The confusion matrix for the classification for a 1000 test image dataset and 3500 image training dataset (selected samples) has been depicted.

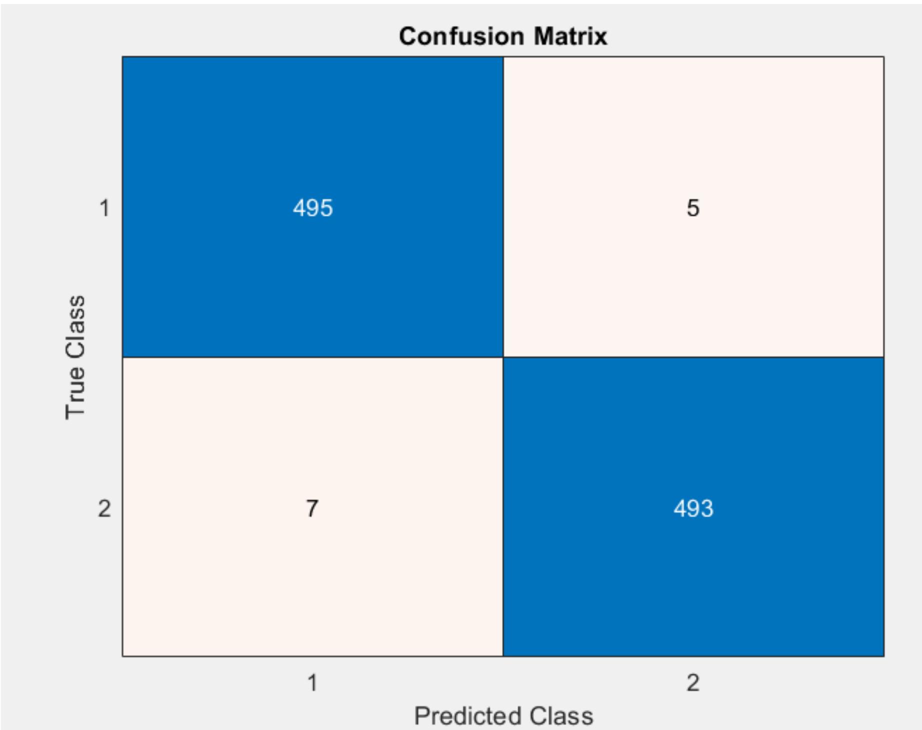

Fig.10 Confusion Matrix for Image Classification

Figure 10 depicts the confusion matrix for the model.

Table 2. Performance Metrics

Accuracy	Sensitivity Or Recall	Precision	F-Measure
0.988	0.99	0.986	0.987

The proposed approach attains an accuracy of 0.988, sensitivity or recall value of 0.99, specificity of 0.986, precision of 0.9736 and F-Measure of 0.987

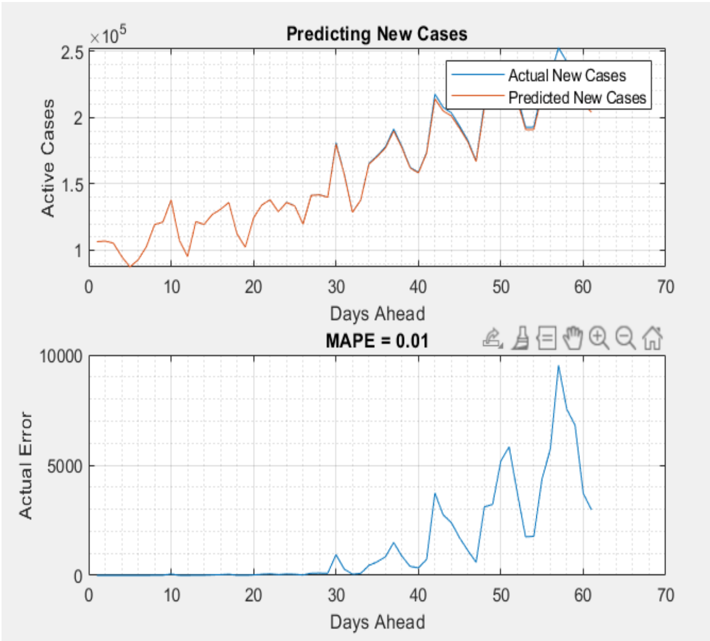

Fig.11 Raw Data

Figure 11 depicts the raw time series data for the active number of future cases over a 188-day period from January 2020 to July 2020. Figure 11 depicts the forecasting MAPE for the proposed approach which happens to be only 0.01%.

A detailed comparative analysis is presented separately for image classification, future cases prediction, is presented subsequently.

Table 3 Comparative Analysis with previous work

Authors	Publication	Approach	Findings
Rashid et al.	Springer 2023	Analysis of novel Coronavirus using machine learning approaches.	The average accuracy of 92.9% achieved with the assistance of supervised machine learning methods such as neural networks and logistic regression.
Akbarimaj det al.	Elsevier 2022	Convolutional Neural Network (CNN) with noise map layer to identify noisy and non-noisy pixel regions, for accurate classification	Accuracy of 72% achieved Proposed approach beats ResNet 18 and ResNet 50 by 2%

Pathan et al.	Elsevier 2021	Performance evaluation of common deep learning models such as: AlexNet, VGG-16, GoogleNet, MobileNet-V2, SqueezeNet, ResNet-34, ResNet-50 and Inception-V3 done.	Highest classification accuracy of 96.33% achieved with ResNet 34.
Gannour et al.	IEEE 2020	Deep Learning Models VGGNet, InceptionNet, ExceptionNet, ResNet and MobileNet employed.	Highest accuracy of 97% attained with InceptionNet with ADAM optimizer.
Xu et al.	Elsevier 2022	Regression model based on CNN-LSTM ensemble model.	MAPE of 2.49% (Best Case)
Balli et al.	Elsevier 2021	Regression models based on RF, LR, MLP and SVM	MAPE of 2.0762 (RF) 0.1853 (LR) 0.8179 (MLP) 0.1247 (SVM)
Proposed Approach		**DWT+PCA+ Deep Net with Bayesian Optimization**	**Iterative noise removal followed by extraction of 12 image features used to train the designed BayesNet model which attains a classification accuracy of 98.8%** **Forecasting MAPE of 0.01%**

A comparative analysis with existing work clearly indicates that the proposed system outperforms baseline contemporary models such as CNN, CNN-LSTM, ImageNet, SVM, RF etc. both in terms of classification accuracy as well as forecasting MAPE.

CONCLUSION

It can be concluded from previous discussions that machine learning and deep learning are transforming the health care sector, offering innovative solutions to complex medical challenges. From improving diagnostic accuracy to enabling personalized medicine, these technologies are driving a paradigm shift in how care is delivered and managed. Although challenges exist, the ongoing advancements in ML and DL will continue to reshape the health care landscape, ultimately benefiting patients and providers alike. Investing in these technologies today will pave the way for a healthier, smarter future. This paper presents a model comprising of data filtration based on DWT, dimensional optimization using the PCA and pattern recognition based on a deep neural network approach. The probabilistic Bayesian regularization algorithm is used for training the model. It can be observed that the proposed model comprising of denoising, dimensional optimization and probabilistic optimization in training outperforms exiting approaches in terms of performance metrics.

REFERENCES

[1] K. Shailaja, B. Seetharamulu and M. A. Jabbar, "Machine Learning in Healthcare: A Review," 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 2018, pp. 910-914.

[2] M. Chen, Y. Hao, K. Hwang, L. Wang and L. Wang, "Disease Prediction by Machine Learning Over Big Data From Healthcare Communities" in IEEE Access 2017, vol. 5, pp. 8869-8879.

[3] A. Qayyum, J. Qadir, M. Bilal and A. Al-Fuqaha, "Secure and Robust Machine Learning for Healthcare: A Survey," in IEEE Reviews in Biomedical Engineering, 2021,vol. 14, pp. 156-180

[4] J. Miah, R. H. Khan, S. Ahmed and M. I. Mahmud, "A comparative study of Detecting Covid 19 by Using Chest X-ray Images– A Deep Learning Approach," 2023 IEEE World AI IoT Congress (AIIoT), Seattle, WA, USA, 2023, pp. 0311-0316

[5] A. Hussain, S. U. Amin, H. Lee, A. Khan, N. F. Khan and S. Seo, "An Automated Chest X-Ray Image Analysis for Covid-19 and Pneumonia Diagnosis Using Deep Ensemble Strategy," in IEEE Access, 2023, vol. 11, pp. 97207-97220.

[6] S. Mishra and A. Mantri, "Design of COVID19 Detection based on Relative Eccentric Feature Selection using Deep Vectorized Regressive Neural Network for Corona Virus," 2023 IEEE International Conference on Integrated Circuits and Communication Systems (ICICACS), Raichur, India, 2023, pp. 1-6.

[7] J Somasekar, PP Kumar, A Sharma, “Machine learning and image analysis applications in the fight against COVID-19 pandemic: Datasets, research directions, challenges and opportunities”, Proceedings in Matrials Today, Elsevier 2021.

[8] J. De Moura et al., "Deep Convolutional Approaches for the Analysis of COVID-19 Using Chest X-Ray Images From Portable Devices," in IEEE Access, 2020, vol. 8, pp. 195594-195607.

[9] S Kumar, RD Raut, BE Narkhede,” A proposed collaborative framework by using artificial intelligence-internet of things (AI-IoT) in COVID-19 pandemic situation for healthcare workers”, International Journal of Healthcare Management, Taylor and Francis, 2020, vol.13, no.4, pp. 337-345.

[10] JB Awotunde, SO Folorunso, RG Jimoh, “Application of artificial intelligence for COVID-19 epidemic: an exploratory study, opportunities, challenges, and future prospects”, Artificial Intelligence for COVID-19. Studies in Systems, Decision and Control, Springer, 2021, vol 358.

[11] S. Hu et al., "Weakly Supervised Deep Learning for COVID-19 Infection Detection and Classification From CT Images," in IEEE Access, 2020, vol. 8, pp. 118869-118883.

[12] J. C. Clement, V. Ponnusamy, K. C. Sriharipriya and R. Nandakumar, "A Survey on Mathematical, Machine Learning and Deep Learning Models for COVID-19 Transmission and Diagnosis," in IEEE Reviews in Biomedical Engineering, 2022, vol. 15, pp. 325-340

[13] H. S. Alghamdi, G. Amoudi, S. Elhag, K. Saeedi and J. Nasser, "Deep Learning Approaches for Detecting COVID-19 From Chest X-Ray Images: A Survey," in IEEE Access, 2021, vol. 9, pp. 20235-20254.

[14] T Ozturk, M Talo, EA Yildirim, UB Baloglu, “Automated detection of COVID-19 cases using deep neural networks with X-ray images”, Computers and Biology and Medicine, Elsevier 2020, col.121, 103792.

[15] M. M. Islam, F. Karray, R. Alhajj and J. Zeng, "A Review on Deep Learning Techniques for the Diagnosis of Novel Coronavirus (COVID-19)," in IEEE Access, vol. 9, pp. 30551-30572.

[16] A Akbarimajd, N Hoertel, MA Hussain, “Learning-to-augment incorporated noise-robust deep CNN for detection of COVID-19 in noisy X-ray images”, Journal of Computational Science, Elsevier 2022, vol.63, 101763.

[17] MR Hassan, WN Ismail, A Chowdhury, “A framework of genetic algorithm-based CNN on multi-access edge computing for automated detection of COVID-19”, The Journal of Supercomputing, Springer 2022, vol.78, pp.10250–10274.

[18] ML Huang, YC Liao, “A lightweight CNN-based network on COVID-19 detection using X-ray and CT images”, Computers in biology and medicne, Elsevier 2022, vol.146, 105604.

[19] MF Aslan, K Sabanci, A Durdu, MF Unlersen, “COVID-19 diagnosis using state-of-the-art CNN architecture features and Bayesian Optimization”, Computers in biology and Medicine, Elsevier 2022, vol.142, 105244.

[20] MF Aslan, MF Unlersen, K Sabanci, A Durdu, “CNN-based transfer learning–BiLSTM network: A novel approach for COVID-19 infection detection”, Applied Soft Computing, Elsevier 2021, vol.98, 106912.

[21] R Kundu, PK Singh, S Mirjalili, R Sarkar, “COVID-19 detection from lung CT-Scans using a fuzzy integral-based CNN ensemble”, Computers in biology and medicine, Elsevier 2022, vol.138, 104895.

[22] S Pathan, PC Siddalingaswamy, T Ali, “Automated Detection of Covid-19 from Chest X-ray scans using an optimized CNN architecture”, Biomedical Signal Processing and Control, Elsevier, 2022, vol.64, 102365.

[23] NN Das, N Kumar, M Kaur, V Kumar, D Singh, “Automated deep transfer learning-based approach for detection of COVID-19 infection in chest X-rays”, IBRM, Elsevier, 2022, vol.43, no.2, pp.114-119.

[24] D. A. Zebari, A. M. Abdulazeez, D. Q. Zeebaree and M. S. Salih, "A Fusion Scheme of Texture Features for COVID-19 Detection of CT Scan Images," 2020 International Conference on Advanced Science and Engineering (ICOASE), 2020, pp. 1-6.

[25] O. El Gannour, S. Hamida, B. Cherradi, A. Raihani And H. Moujahid, "Performance Evaluation of Transfer Learning Technique for Automatic Detection of Patients with COVID-19 on X-Ray Images," 2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS), 2020, pp. 1-6.

[26] M Momeny, AA Neshat, MA Hussain, S Kia, “Learning-to-augment strategy using noisy and denoised data: Improving generalizability of deep CNN for the detection of COVID-19 in X-ray images”, Computers in Biology and Medicine, Elsevier 2021, vol.136, 104704.

[27] S Surono, MYF Afitian, A Setyawan, D. Arofah, A. Thobirin “Comparison of CNN Classification Model using Machine Learning with Bayesian Optimizer”, HighTech and Innovation Journal 2023, vol.4, no.3, pp.1-12.

[28] AS Kwekha-Rashid, HN Abduljabbar, B Alhayani, “Coronavirus disease (COVID-19) cases analysis using machine-learning applications”, Applied Nanoscience, Springer, 2023, vol.31, pp. 2013–2025.

[29] Y Zhang, Q Zhang, Y Zhao, Y Deng, H Zheng, “Urban spatial risk prediction and optimization analysis of POI based on deep learning from the perspective of an epidemic”, International Journal of Applied Earth Observation and Geoinformation, , Elsevier, 2022, vol. 112, 102942.

[30] A Mollalo, B Vahedi, S Bhattarai, LC Hopkins, “Predicting the hotspots of age-adjusted mortality rates of lower respiratory infection across the continental United States: Integration of GIS, spatial statistics and machine learning algorithms”, International Journal of Medical Informatics, Elsevier, 2021, vol. 142, 104248.

[31] SD Khan, L Alarabi, S Basalamah -, “Toward Smart Lockdown: A Novel Approach for COVID-19 Hotspots Prediction Using a Deep Hybrid Neural Network”, Journal of Computers, MDPI, 2020, vol.9, no.9, pp1-16.

[32] L Xu, R Magar, AB Farimani, “Forecasting COVID-19 new cases using deep learning methods”, Computers in biology and medicine, Elsevier 2022, vol.144, 105342

[33] S Ballı, “Data analysis of Covid-19 pandemic and short-term cumulative case forecasting using machine learning time series methods”, Chaos, Solitons & Fractals, Elsevier, 2021, vol.142, 110512.

[34] A. Waheed, M. Goyal, D. Gupta, A. Khanna, F. Al-Turjman and P. R. Pinheiro, "CovidGAN: Data Augmentation Using Auxiliary Classifier GAN for Improved Covid-19 Detection, " in IEEE Access, vol. 8, pp. 91916-91923, 2020

[35] C. Zhou, J. Song, S. Zhou, Z. Zhang and J. Xing, "COVID-19 Detection Based on Image Regrouping and Resnet-SVM Using Chest X-Ray Images," in IEEE Access, vol. 9, pp. 81902-81912, 2021.

[36] L. Xiao, Z. Zhang, K. Huang, J. Jiang and Y. Peng, "Noise Optimization in Artificial Neural Networks," in IEEE Transactions on Automation Science and Engineering, doi: 10.1109/TASE.2024.3384409.

[37] S. Nie, M. Zheng and Q. Ji, "The Deep Regression Bayesian Network and Its Applications: Probabilistic Deep Learning for Computer Vision," in IEEE Signal Processing Magazine, vol. 35, no. 1, pp. 101-111.

[38] X. Wu, D. Hong and J. Chanussot, "Convolutional Neural Networks for Multimodal Remote Sensing Data Classification," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-10.