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The Impact of AI in COVID-19: AI-Powered Diagnostics, Epidemiology

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ABSTRACT: The COVID-19 epidemic commenced in December 2019 in Wuhan, China. In contrast to the Spanish flu pandemic of 1918, the death rate from COVID-19 is merely 5%. The condition is caused by the Severe Acute Respiratory Syndrome Coronavirus 2 strain. In reaction to this catastrophe, several nations have implemented quarantines to mitigate the worldwide dissemination of the COVID-19 virus. COVID-19 vaccines will not be accessible until December 2020. A dependable identification method is essential for the early detection of COVID-19 to preserve humanity. Recent studies indicate that Chest X-ray (CXR) imaging is the most expedient way for diagnosing and classifying COVID-19, and it is also more reliable than Reverse Transcription Polymerase Chain Reaction (RT-PCR) as it yields critical information regarding the coronavirus. Clinical practitioners may initiate treatment at the preliminary stage based on this CXR diagnosis. This article proposes methods for predicting the spread of the COVID-19 pandemic utilizing GLCM-CNN, a deep learning system.

KEYWORDS- Deep Learning, Chest X-Ray Analysis, GLCM, CNN, Covid-19 Prediction, Accuracy, Precision, Recall

I. INTRODUCTION

The emergence of novel coronavirus (COVID-19) infections has generated significant worry. The Middle East respiratory syndrome coronavirus (MERS-CoV), responsible for moderate to mild respiratory illnesses, was originally identified in Saudi Arabia in 2012 and has subsequently disseminated throughout the nation [1]. Complications arising from a MERS-CoV infection can be fatal. A significant number of individuals have succumbed to the severe acute respiratory illness induced by MERS-CoV. Al-Turaiki and associates documented that MERS-CoV can induce a range of symptoms, such as a chronic cough, elevated body temperature, nasal congestion, respiratory distress, and diarrhea [2]. The World Health Organization formally designated the ensuing disease as 'COVID-19' on February 11, 2020. Chinese health authorities have identified more than 10,000 COVID-19 cases. The illness seems to be disseminating across the nation from individual to individual. The United States is one of the growing number of countries that have documented COVID-19 cases, primarily attributed to travel from Wuhan.

Artificial intelligence (AI) is increasingly being utilized in the medical sector. Recent advancements in digital data collecting, machine learning, and computing infrastructure have enabled artificial intelligence (AI) applications to penetrate domains once deemed reliant on human expertise. Few researchers have employed data mining techniques utilizing actual COVID datasets, such as MERS-CoV, alongside various machine learning classifiers. Nonetheless, developing predictive systems that consistently detect and diagnose these illnesses continues to be a problem [3] [4]. To enhance the prediction, prevention, and detection of future global health problems, it is imperative to develop AI-driven methodologies for the early identification of epidemiological threats. Supplementary material concerning the CoV family and the methodologies employed in prior research for prediction, regression, and classification within this context was provided by publications on data mining and machine learning techniques. Researchers in the machine learning literature are addressing questions regarding the diverse applications, assessment, and utilization of machine learning and data mining, as well as the validity of algorithms in their implementation [5].

A procedure termed "image processing" is utilized to extract significant information from photographs. Smart transportation, autonomous visual control systems, biomedical imaging, defense surveillance, remote sensing, and the monitoring of moving objects are all domains that depend on image processing. Digital images are compromised by noise throughout the collection and transmission phases due to flaws in the imaging process. Typically, when sound is included into an image, certain pixels are substituted with those from the original picture. The original pixel value is modified by the addition or subtraction of the values of the supplementary pixels [6].

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Radiological imaging is one of the most effective screening methods for diagnosing COVID-19. Evidence indicates that the radiological manifestation of pneumonia resulting from COVID-19 aligns with its clinical progression; nearly all patients diagnosed with the virus exhibit consistent CT scan abnormalities, including early-stage ground-glass opacities and later-stage lung consolidation [7] [8]. The configuration and arrangement of the lungs in the periphery may be rounded. AI can be employed to do an initial assessment of a COVID-19 patient, serving as an alternative to labor-intensive and time-consuming traditional approaches. We present an AI-driven approach for anticipating COVID-19 cases and diagnosing patients using chest X-rays. Numerals 6 to 8 Employing computed tomography (CT) or computed radiography (CXR) to identify a Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) infection represents one possible diagnostic method. The radiologist can evaluate the progression of the viral infection in the lungs using CT and CXR images. The utilization of high-resolution images for classification is essential for precise COVID-19 diagnosis; yet, the dataset is the most significant challenge. Through the comparison of CXR and CT scans, we obtained images with abundant characteristics.

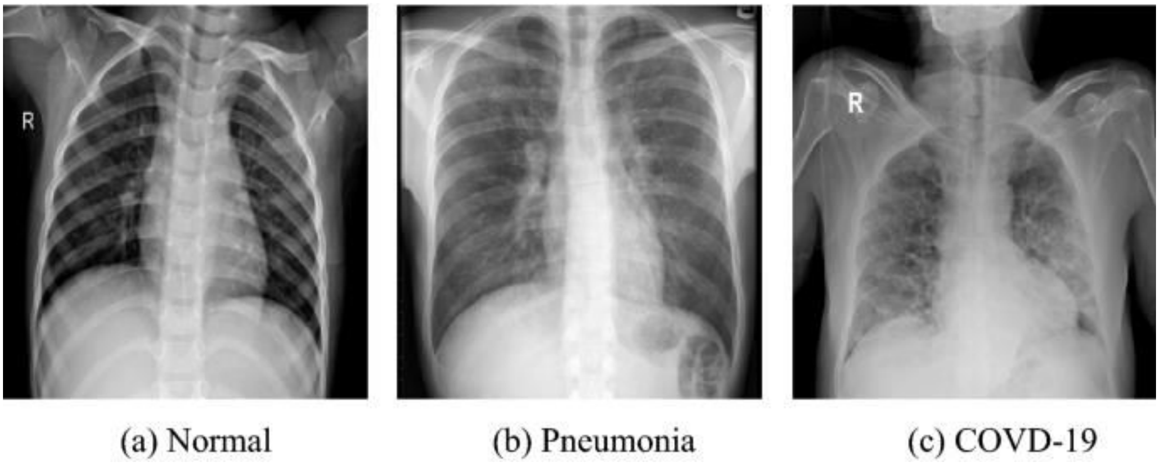

Figure 1: (a) Normal case, (b) Pneumonia case, and (c) COVID-19 case.

Artificial intelligence is executed using machine learning. Machine learning (ML) is most efficacious when trained on a moderate quantity of organized data, producing results that align with the problem's specifications. Machine learning operates effectively on any system, irrespective of the hardware or software employed. Machine learning necessitates less time for data preparation prior to training and analysis. To enhance the efficiency and accuracy of result analysis, it diminishes data complexity. It utilizes the divide-and-conquer methodology to evaluate data and get findings; it commences by identifying patterns, hence fragmenting a problem into subproblems, as it is more manageable to obtain an output from a smaller issue. Ultimately, it aggregates the results to obtain the ultimate outcome. [9]

The extraction of characteristics for model development is a critical phase in the automated detection of Covid-19 and associations from extensive data repositories. A feature typically offers a suitable representation by delineating a characteristic extracted from the raw input data. The objective of feature extraction is to identify variance elements that are crucial to the learning process while maintaining discriminatory information. Within the aquatic environment The effectiveness of the extraction process is crucial for the performance of machine learning, as it relies heavily on precisely described features.

The advancement of increasingly adaptable data sources has led to the creation of numerous feature extraction methods. For example, to study CXR images, it is customary to employ techniques that extract data from the temporal domain (including range, skewness, and mean) and the frequency domain (such as frequency bands). The application-specific engineering process sometimes requires extensive domain knowledge, rendering manual feature design a challenging and time-intensive task. This is the reason individuals perceive it as inflexible, laborious, and sluggish. These are the principal challenges and issues associated with machine learning methodologies. We require deep learning methodologies to address these issues and surmount these obstacles. Fortunately, deep neural networks may overcome this limitation of manually designed characteristics. Their advanced design enables the automation of feature learning and the extraction of discriminative feature representations with minimal to no human involvement. This elucidates why deep learning is superior in processing vast quantities of noisy, unstructured data. In a conventional hierarchical feature learning approach, foundational features are utilized to develop

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more abstract higher-level features. Various feature learning procedures, in conjunction with model construction, are accessible based on the data type and the selected deep learning architecture [10].

II. LITERATURE SURVEY

Although radiography scans are the most reliable method for distinguishing coronavirus pneumonia from other types of viral pneumonia, there is still need for improvement in the correct interpretation of imaging features [10]. The accuracy of COVID diagnoses could be severely compromised if radiological images (CT and X-ray) are misinterpreted because of inaccurate, unclear, or noisy datasets. Many problems, including duplicate data and missing values, make it difficult to train ML/DL algorithms. Consequently, scientists started training viral detection systems using a range of datasets. A final chest picture is created by combining numerous images taken from different angles, as opposed to the time-consuming and expensive C.T. scan. In the past, studies have shown that employing a CT image-based model can achieve an AUC of 0.86 and an accuracy of 99.96% at its most extreme.

A number of ML algorithms have achieved impressive gains in the diagnosis of various diseases when applied to medical datasets. The field of computer science known as artificial intelligence (AI) focusses on teaching computers to learn and construct complicated models [11]. Deep learning, or DL, is an arsenal of algorithms that, when combined, provide an expert system with the ability to identify problems and forecast their outcomes. A computer equipped with pattern recognition and intelligent decision-making capabilities is the result of ML and DL algorithms [12]. Many ML/DL algorithms have been employed for problem detection, forecasting, and diagnosis of Coronavirus Type 19.

Data points in each class can have their edges enlarged to points on the hyperplane, and classifiers trained with support vector machines can learn the hyperplane and differentiate instances from each class. Ku-NN is also a supervised approach. In order to classify the unknown sample, we find the K-smallest distance between it and the training samples that came before it. One common usage for these K classes is to identify the unknown class of sample output [13].

One root node, many internal nodes, and a few of terminal nodes make up a decision tree. A set of attributes is connected to a value-displaying branch for every leaf node. The D.T. method's primary objective is to construct a dataset tree and provide improved results for each leaf. Because it uses a combination of decision trees, a Random Forest classifier outperforms a single tree in terms of prediction accuracy. Easy to use and quick to produce accurate predictions, this classifier is suitable for a variety of datasets.

This method seeks for signs of a virus by analyzing samples collected from the nose or throat of an infected person. Reliable results cannot be obtained with RT-PCR because to its high false-positive rate [14]. There is a lack of RT-PCR on a worldwide scale. Furthermore, it is expensive and necessitates much research. This study found that in comparison to previous analyses, the RT-PCR based model had the worst accuracy (at 80%) and the best AUC (at 0.84). Despite having the highest area under the curve (AUC) of 0.97, the clinical blood test-based model had the lowest accuracy (84.24%), according to earlier research. When comparing models based on RT-PCR and clinical blood tests, the AUC of 0.97 [15] is much higher for the former.

A CT scan is more expensive than a C.T. scan but takes much less time to provide an image of the entire chest since it combines images taken from multiple angles. Prior studies found that the C.T. image-based model could reach an accuracy level of 99.96% and a minimum AUC of 0.86.
Getting a chest X-ray can be done in a few different ways. The cost of an X-ray is usually quite affordable. Most medical experts opted to use X-ray photos instead of C.T. images. According to one study, the maximum accuracy achieved with an X-ray imaging model was 99.7 percent, while the lowest was 86.7 percent [16].

The development of ML/DL in recent years has facilitated medical diagnostics, particularly the identification and diagnosis of lung illnesses. Recent studies in radiography have demonstrated that DL approaches are highly successful. C.T. scans and X-rays are two of many imaging modalities that can be employed to identify many diseases, including COVID-19. While X-rays are faster to analyze and save data from, C.T. scanning requires more radiation. The use of computer-aided design (CAD) tools to estimate COVID-19 from low-dose X-ray imaging has the potential to considerably improve and support radiologists' workflow.

There may be research gaps that need to be filled up after analyzing the results. The MERS-CoV dataset was analyzed using three different machine learning methods to determine the most effective classification model. These algorithms took into account both binary class and multiclass labels. The findings show that when dealing with problems with two

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classes, K-NN is the optimal model to use, however when dealing with problems with more than two classes, decision trees and Naive Bayes are the way to go. When it comes to accurately predicting cases of MERS-CoV, the authors show that the decision tree classifier is the best model. Medical practitioners should fare better than the general public based on the prediction model's findings that age and symptoms are the most important factors. Using statistical methods like univariate and multivariate regression, researchers from Saudi Arabia set out to identify the most important aspects impacting human infection. Age, illness severity, healthcare industry employment status, and a history of chronic disease were determined to be the four most important characteristics in the study. Camels do not significantly affect the patient's recuperation [17].

Medical diagnosis algorithms for binary and multiclass challenges in MERS-CoV datasets were the focus of a Saudi Arabian project that ran from 2013 to 2017 and reported its findings in 2017. The experimental results demonstrated that decision tree and support vector machine classifiers performed the best in the MERS-CoV dataset when it came to classifying the multiclass labels. A technique for emotional recognition based on machine learning (ML) was developed in [18] to gain a better understanding of how people react to a global outbreak of infectious diseases like MERS.

By analyzing a Korean dataset acquired in 2015, researchers found that lowering anxiety levels would reduce the likelihood of contracting MERS CoV [19], in which the author used three machine learning algorithms to forecast the virus's spread in persons over the age of 50 who had already contracted the virus. Researchers found that the virus is more common in the elderly compared to younger age groups. The MERS and SARS protein sequences were evaluated and reported in [20] using a sigmoid, normal, and polynomial support vector machine classifier. According to the findings, they were very similar to one another and had many commonalities.

Data mining techniques based on statistical methods and utilizing statistical methodologies have been utilized to develop a cloud-based medical system with high prediction accuracy to prevent the spread of MERS-CoV across geographies [21]. There are several kinds of information contained within the data: treatment, patient, and electronic health record stored in the cloud More infections and diseases can be accurately identified and predicted with the use of artificial intelligence in healthcare [22]. In order to conduct this investigation, we scoured the literature for any and all articles discussing the use of AI for human MERS-CoV and SARS-CoV detection and diagnosis. The necessity and promise of employing AI to foresee COVID-19 outbreaks have been highlighted by the current pandemic. It is possible to build a medical diagnostic system that uses both supervised and unsupervised learning methods to diagnose patients. In this case, we're using MERS-CoV and SARS-CoV as our target classes for each dataset sample; if we find a new disease, we may update the technique to detect it. Even though SARS-CoV and MERS-CoV are in the same cluster, the two viruses are very different. Consequently, clustering based on unsupervised learning is generally regarded as a valuable method for organizing and classifying newly acquired data.

III. METHODOLOGY

Feature extraction using **GLCM (Gray Level Co-occurrence Matrix)** is a popular technique in image processing and computer vision for texture analysis. The core idea behind GLCM is to capture the spatial relationship between pixel values in an image. These relationships help describe the texture properties of the image, such as smoothness, roughness, regularity, or randomness, and they can be used for tasks such as image classification, segmentation, and pattern recognition.

A **Gray Level Co-occurrence Matrix (GLCM)** is a matrix that describes the frequency at which pixel pairs with specific values and a specific spatial relationship occur in an image.

- **Gray Levels**: Refers to the intensity levels in a grayscale image. For instance, an image might have pixel values ranging from 0 (black) to 255 (white), with many shades in between.
- **Spatial Relationship**: Defines how pixels are positioned relative to each other. Typically, it's defined in terms of a **distance** (how far apart the pixels are) and an **angle** (the direction in which the pixel pair is analyzed).

The GLCM is created by sliding a window over the image and counting how often two pixels with certain values appear in a specified spatial relationship.

For example, if the relationship is a distance of 1 pixel and a direction of 0 degrees (horizontal), the matrix counts how often a pixel with intensity value i appears adjacent (horizontally) to a pixel with intensity value j.

SVM is a commonly preferred option for regression and classification tasks. SVM, functioning as a binary classifier, assigns a value of either -1 or 1 to newly-added data points. SVMs utilize a training dataset to classify fresh samples into one of two categories while constructing a model. A support vector machine (SVM) model employs a spatial mapping technique that maximizes the separation between different categories by utilizing as much space as feasible.

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Therefore, by determining which side of the gap a new example falls on, we can make a prediction about which group it belongs to.
Figure 2 depicts the high-dimensional space in which Support Vector Machines (SVM) create a hyperplane to perform classification or regression tasks.
This may be done using a linear discriminant function, such as:

$$(x)=a^t x+b \tag{3}$$

In which a is the weight vector and x is the pattern vector. Thus thediscriminanthyperplaneshouldsatisfythecriterionbelowforalldatapatternsx_i:

$$(x_i)\geq 1 \tag{4}$$

Inthisformula$z_i$representsthelabelwhichcantakeonlyvalue1or-1.

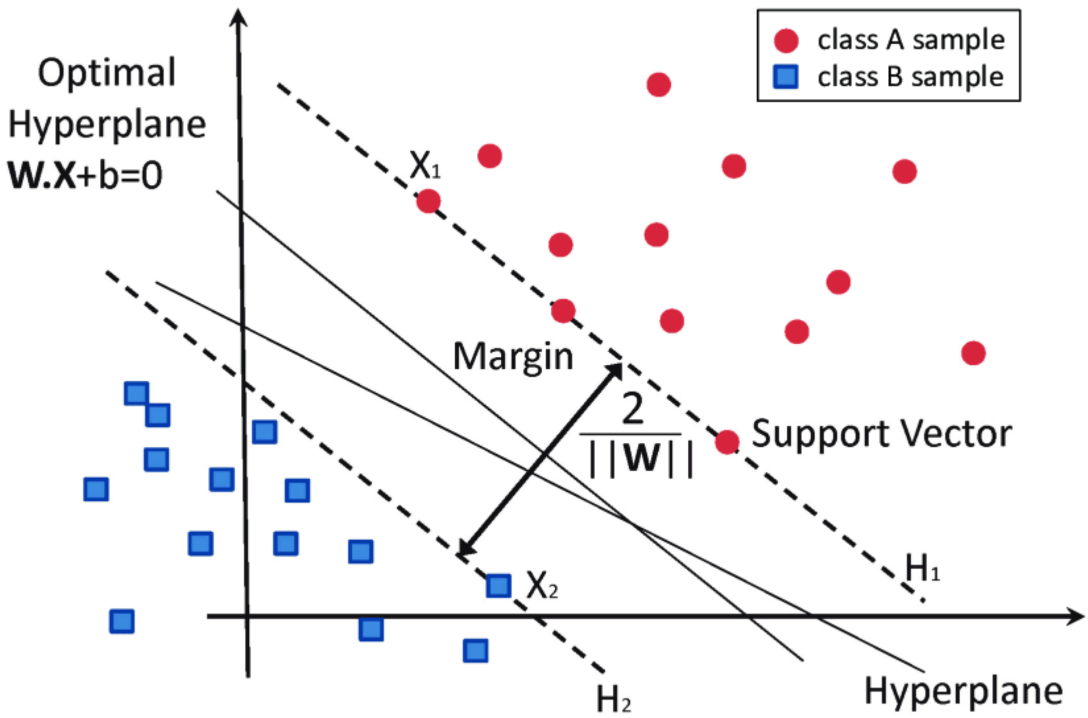

Figure 2 Support Vector Machine

Finding the separating hyperplane with the highest margin is the purpose of training a Support Vector Machine, as shown in Figure 3. We anticipate the classifier to have higher generalization with a bigger margin. Hence, the following optimization problem formulation may be used for SVM training:

$$\frac{z_i(x_i)}{\|a\|}$$

for each data point xi the distance from hyperplane is $zig(x_i)$, and assuming that a positive margin b exists, thus the goal is to find the weight vector$a$suchthatitmaximizesthemargin$b$andminimizesthesize$\|a\|^2$.

An artificial neural network (ANN) is formed by a collection of nodes that resembles the intricate network of neurons seen in the human brain. An Artificial Neural Network (ANN) may modify its structure based on the input it receives, in order to optimize its performance for the whole system or specific nodes. Contemporary neural networks and other

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advanced technologies are already widely used for modeling nonlinear statistical data. Data patterns may be discovered by using them to illustrate complex relationships between inputs and outcomes.

In theory, the output (node j) of a neuron is decided by the weighted sum of its inputs along with a bias (bj). Other sigmoid functions, such as the arctangent and hyperbolic tangent, can be utilized. The specifics of the function do not impact the capabilities of the neural network. In order to train a network, one must provide it with data and then make adjustments to its weights until the network closely approximates the desired function. The result is that the neural network is trained using inputs and subsequently assessed for its responsiveness and the quality of its output. Subsequently, the weights are adjusted in order to minimize the disparity between the anticipated and observed outputs, aiming for a value approaching zero. Iterations are frequently employed to input data into the network and modify its weights. Training a neural network correctly often requires multiple iterations.

It is uncommon to adjust weights during training depending on specific criteria. The fundamental learning approach involves initially introducing a training pattern to an unskilled network and subsequently use the result to direct subsequent training. When the expected and actual outcomes from the network are the same, the criterion function, which is a sum of the weights multiplied by their respective values, is decreased.

A type of deep learning method is convolutional neural networks (CNNs), which accept an image as input, classify objects within the image based on their distinctive properties, and subsequently distinguish between them using biases and learnable weights. Although the fundamental approach entails manual filter engineering, CNN can acquire these characteristics through validation. The pre-processing required for CNNs and the various classification algorithms are not strongly connected. Convolutional Neural Networks (CNN), a prominent category of deep learning architectures, depend on their shared weights configuration and trait of translation invariance. Convolutional neural networks (CNNs) simplify complex patterns into basic structures while maintaining spatial relationships through domain expertise. A convolutional neural network (CNN) has an input layer, an output layer, and many hidden layers. Examples of hidden layers include multiple convolutional layers, pooling layers, and normalization layers. Ultimately, there exist entirely connected layers. The interconnection of each node to every node in all other layers results in a system that is intricate and potentially wasteful. The Rectified Linear Unit (ReLU) activation function operates within the convolutional neural network (CNN). The activations from preceding layers are convolved with specified 3x3 filters during the activation of the convolution layer. When all layers and nodes converge on identical weights, the computation of weights is significantly simplified. The outputs of the convolution layer are aggregated by a pooling layer. The surveying layer generates a singular outcome for diminutive lattices by max-pooling or average pooling. Translational invariance is achieved post-pooling layer to prevent shifts in activation maps due to input alterations. Down-sampled pooling simplifies the model by augmenting the stride length of the convolution.

The neural network employs stochastic sampling to implement dropout regularization. Various iterations yield distinct outputs due to the elimination of different neurons. The weights are routinely adjusted to attain improved results. For each training batch, the normalized batch output is derived by dividing the activation maps by the standard deviations and subsequently subtracting the mean. Figure 3 illustrates the CNN design. The image is directly input into the model. The convolution layer extracts information such as colors, borders, and corners from the input image. The characteristics of plaque structure, kurtosis, texture, and non-plaque area are derived from deeper layers at greater depths. The pooling layer extracts the most significant features from the localized neighborhood. In max pooling, an example-based discretization technique, the down-sampled window is populated with the most extreme values from each segment of the feature map. By incorporating translational invariance into the internal model at a manageable computational expense, max-pooling demonstrates its functionality as illustrated in Figure 4. The appropriate element space is diminished through pooling and replacement convolution layers. Subsequent layers enhance the categorization process and improve accuracy by extracting additional disease-related information.

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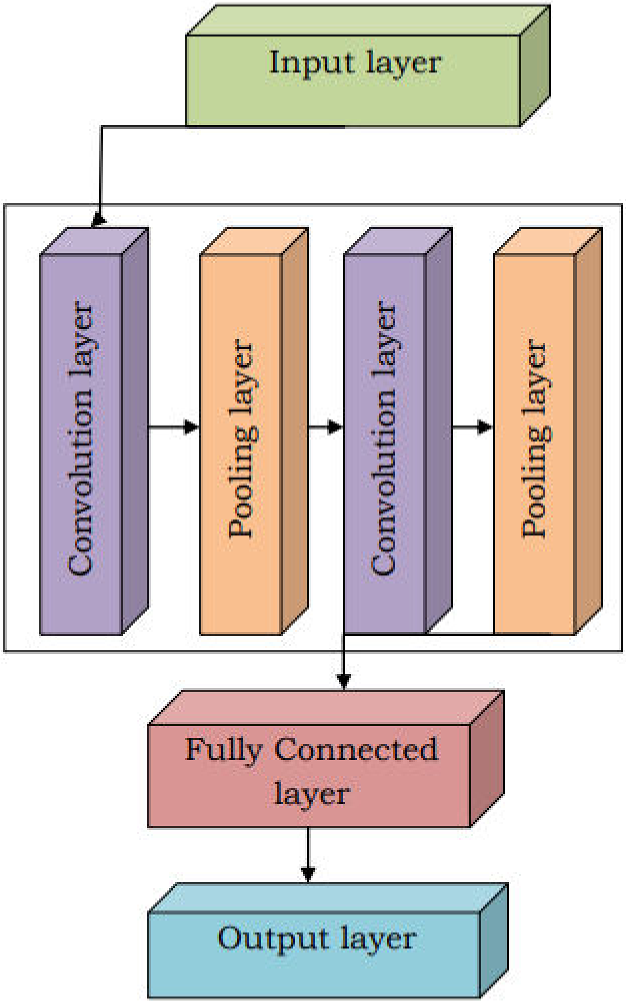

Figure 3- CNN Architecture

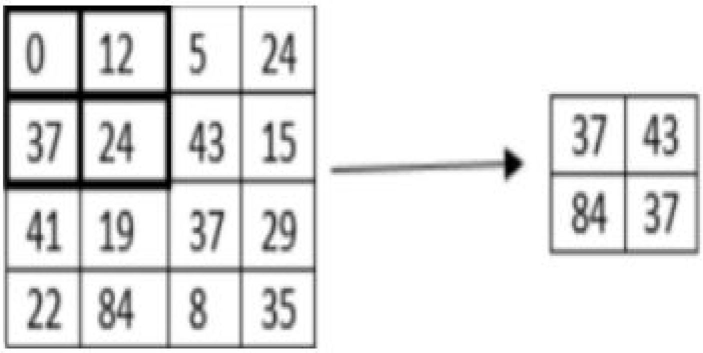

Figure 4: Max Polling Operation Feature Map

After pooling and convolution, the data is converted into a column vector that may be used in multi-level fully connected architectures. A feedforward neural network and back propagation architecture follow in subsequent training iterations. Once the dominating and low-level traits have been correctly determined, classification can proceed.

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IV.RESULT ANALYSIS

This inquiry acquired many datasets from various sources. The datasets include the COVID-19 X-ray dataset, the CoronaHack-chest X-ray dataset, the COVID-radiology database, and the COVID-19 X-ray database. The Kaggle community selected the COVID-19 Radiography database from the COVID-19 dataset [23]. This dataset has 180 pictures. Of the total images, 4 are classified as normal, 74 are linked to pneumonia, and 20 are linked to COVID-19. This study executed the proposed CNN using an Intel i7 CPU and GPU utilizing MATLAB version 2020a. The four quantitative criteria employed to evaluate the proposed models were area under the curve (AUC), recall, accuracy, and precision. In the validation of deep learning models, accuracy, precision, and recall are the most pertinent measures.

Accuracy= (TP + TN) / (TP + TN + FP + FN)
Sensitivity = TP/ (TP + FN)
Specificity = TN/ (TN + FP)

The accurately classified category is denoted by true positive (TP) and true negative (TN), while the incorrectly classified category is indicated by false negative (FN) and false positive (FP). Data accuracy is optimal only when the quantities of false negatives and false positives are same. Precision, a metric of accuracy, considers both the quantity of true positive data and the number of false positives. A high degree of accuracy in the model is unavoidable when there is a high degree of precision. To identify the negative prediction, recollection examined the data pertaining to false negative values.

The accuracy, sensitivity and specificity of machine learning algorithms are shown below in figure 5 and Table 1. The CNN algorithm is performing better on all the comparison parameters.

Table 1: Summary of Results in Percentage

Model	Accuracy	Precision	Recall
SVM	91.3	91.5	93.2
ANN	92.4	92.5	92.6
GLCM-CNN	95.6	96.7	95.34

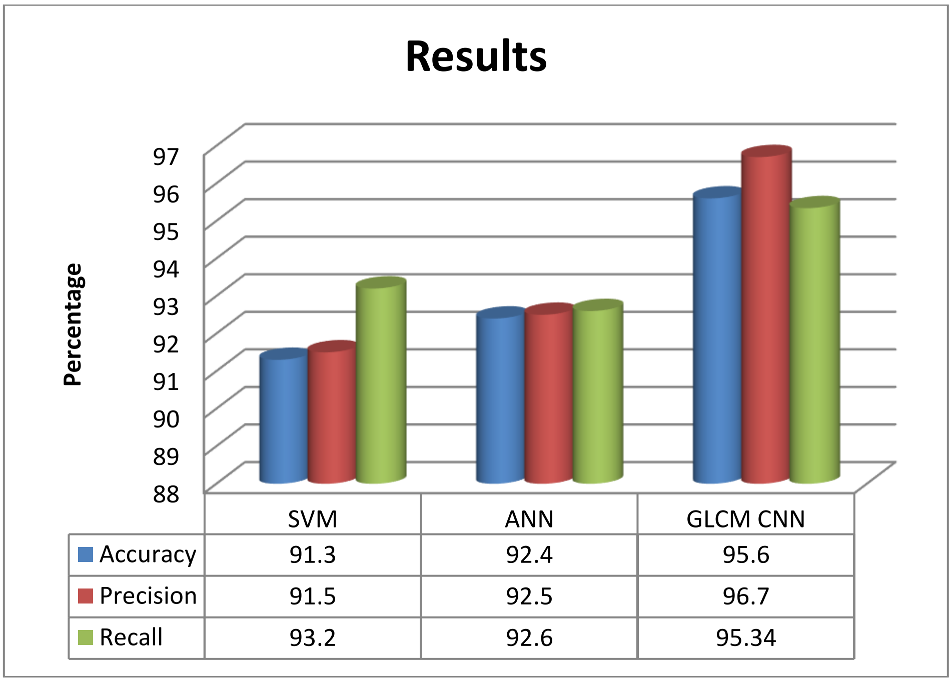

Figure 5: Performance Comparison of CNN for Covid 19 Prediction

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V. CONCLUSION

In order to save humanity from COVID-19, an accurate identification process is required for early detection. According to this research, chest X-ray (CXR) imaging gives critical information about the coronavirus and is more reliable and faster than reverse transcription polymerase chain reaction (RT-PCR) for diagnosing and classifying COVID-19. Machine learning techniques were used extensively in the construction of COVID-19 prediction models. However, deep learning is included in this model due to its vast data access capabilities, which allow for feature extraction automatically. These traits are then used to classify pictures. Medical practitioners can begin treatment in the early stages after receiving this CXR diagnosis. The primary purpose of this work is to offer a methodology for swiftly and accurately detecting COVID-19 utilizing chest X-ray images. This model uses four different kinds of datasets: normal, COVID-19, bacterial pneumonia, and viral pneumonia. The Covid-19 dataset is crucial since it includes official findings from medical testing (RT-PCR) and radiological examinations (chest X-ray). In this paper, we introduce GLCM-CNN, a deep learning system, as a potential tool for COVID-19 pandemic prediction. The CNN algorithm outperforms all other comparative metrics.

REFERENCES

[1] Zhao, S.; Lin, Q.; Ran, J.; Musa, S.S.; Yang, G.;Wang,W.; Lou, Y.; Gao, D.; Yang, L.; He, D.; et al. Preliminary estimation of the basic reproduction number of novel coronavirus (2019-nCoV) in China, from 2019 to 2020: A data-driven analysis in the early phase of the outbreak. Int. J. Infect. Dis. 2020, 92, 214–217. [
[2] Wang, L., Lin, Z. Q., & Wong, A. (2019). "COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images." Scientific Reports, 10(1), 19549.DOI: 10.1038/s41598-020-76523-9
[3] Rajpurkar, P., Irvin, J., & Chen, E. (2019). "Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNet algorithm to practicing radiologists." PLOS Medicine, 16(11), e1002686.DOI: 10.1371/journal.pmed.1002686
[4] Hemdan, E. E. D., Shouman, M. A., & Karar, M. E. (2020). "COVIDX-Net: A framework of deep learning classifiers to diagnose COVID-19 in X-ray images." Computer Methods and Programs in Biomedicine, 196, 105032.DOI: 10.1016/j.cmpb.2020.105032
[5] Chen, N.; Zhou, M.; Dong, X.; Qu, J.; Gong, F.; Han, Y.; Qiu, Y.; Wang, J.; Liu, Y.; Wei, Y.; et al. Epidemiological and clinicalcharacteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: A descriptive study. Lancet 2020, 395, 507–513.
[6] Wu, F.; Zhao, S.; Yu, B.; Chen, Y.-M.; Wang, W.; Song, Z.-G.; Hu, Y.; Tao, Z.-W.; Tian, J.-H.; Pei, Y.-Y.; et al. A new coronavirus associated with human respiratory disease in China. Nature 2020, 579, 265–269.
[7] Guan,W.-J.; Ni, Z.-Y.; Hu, Y.; Liang,W.-H.; Ou, C.-Q.; He, J.-X.; Liu, L.; Shan, H.; Lei, C.-L.; Hui, D.S.; et al. Clinical Characteristics of Coronavirus Disease 2019 in China. N. Engl. J. Med. 2020, 382, 1708–1720.
[8] Wang, D.; Hu, B.; Hu, C.; Zhu, F.; Liu, X.; Zhang, J.; Wang, B.; Xiang, H.; Cheng, Z.; Xiong, Y. Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus–infected pneumonia in Wuhan, China. JAMA 2020, 323, 1061–1069.
[9] Wang, C.; Horby, P.W.; Hayden, F.G.; Gao, G.F. A novel coronavirus outbreak of global health concern. Lancet 2020, 395, 470–473
[10] Zhu, N.; Zhang, D.; Wang, W.; Li, X.; Yang, B.; Song, J.; Zhao, X.; Huang, B.; Shi, W.; Lu, R.; et al. A Novel Coronavirus from Patients with Pneumonia in China, 2019. N. Engl. J. Med. 2020, 382, 727–733.
[11]Wang, S.; Zha, Y.; Li, W.; Wu, Q.; Li, X.; Niu, M.; Wang, M.; Qiu, X.; Li, H.; Yu, H.; et al. A fully automatic deep learning system for COVID-19 diagnostic and prognostic analysis. Eur. Respir. J. 2020, 56.
[12] Thenault, R.; Kaulanjan, K.; Darde, T.; Rioux-Leclercq, N.; Bensalah, K.; Mermier, M.; Khene, Z.-E.; Peyronnet, B.; Shariat, S.; Pradere, B.; et al. The Application of Artificial Intelligence in Prostate Cancer Management—What Improvements Can Be Expected? A Systematic Review. Appl. Sci. 2020, 10, 6428.
[13] Yassin, N.I.; Omran, S.; El Houby, E.M.; Allam, H. Machine learning techniques for breast cancer computer aided diagnosis using different image modalities: A systematic review. Comput. Methods Progr. Biomed. 2018, 156, 25–45.
[14] Das, N.N.; Kumar, N.; Kaur, M.; Kumar, V.; Singh, D. Automated deep transfer learning-based approach for detection of COVID-19 infection in chest X-rays. IRBM 2020.
[15] Kukar, M.; Gunˇcar, G.; Vovko, T.; Podnar, S.; ˇ Cernelˇc, P.; Brvar, M.; Zalaznik, M.; Notar, M.; Moškon, S.; Notar, M. COVID-19 diagnosis by routine blood tests using machine learning. arXiv 2020, arXiv:2006.03476.
[16] Chowdhury, M.E.; Rahman, T.; Khandakar, A.; Mazhar, R.; Kadir, M.A.; Mahbub, Z.B.; Islam, K.R.; Khan, M.S.; Iqbal, A.; Al Emadi, N.; et al. Can AI help in screening viral and COVID-19 pneumonia? IEEE Access 2020, 8, 132665–132676.

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[17] I. Al-Turaiki, M. Alshahrani, and T. Almutairi, "Building predictive models for MERS-CoV infections using data mining techniques," J. Infect. Public Health, vol. 9, no. 6, pp. 744–748, 2016.
[18] S. Choi, J. Lee, M. G. Kang, H. Min, Y. S. Chang, and S. Yoon, "Large-scale machine learning of media outlets for understanding public reactions to nation-wide viral infection outbreaks," Methods, vol. 129, pp. 50–59, 2017.
[19] M. Abdullah, M. S. Altheyab, A. M. A. Lattas, and W. F. Algashmari, "MERS-CoV disease estimation (MDE) A study to estimate a MERS-CoV by classification algorithms," in Communication, Management and Information Technology Proceedings of the International Conference on Communication, Management and Information Technology, ICCMIT 2016, 2017, pp. 633–638.
[20] S. Jang, S. Lee, S. M. Choi, J. Seo, H. Choi, and T. Yoon, "Comparison between SARS CoV and MERS CoV Using apriori algorithm, decision tree, SVM," in MATEC Web Conf., 2016, vol. 49, p. 8001.
[21] R. Sandhu, S. K. Sood, and G. Kaur, "An intelligent system for predicting and preventing MERS-CoV infection outbreak," J. Supercomput., vol. 72, no. 8, pp. 3033–3056, 2016.
[22] J. B. Long and J. M. Ehrenfeld, "TheRoleofAugmented Intelligence (AI) in Detecting and Preventing the Spread of Novel Coronavirus," J. Med. Syst., vol. 44, no. 3, p. 59, 2020.
[23] https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia