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Block Matching and 3D Filtering (BM3D) for Preprocessing of CT scans of Covid-19 Lung Images

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ABSTRACT
SARS-CoV2 or the Corona Virus 2 is the cause of the global Corona Virus illness 2019 epidemic, also known as the COVID-19 pandemic (SARS-CoV-2). Wavelets are mostly used for denoising a two-dimensional signal for images mostly and so we have adopted a Discrete Wavelet Transform for CT image of covid and healthy lung images. Block Matching and 3D filtering can give better performance for pre-processing. Evaluation parameters such as SSIM, CC and NCC are considered for DWT and BM3D methods for Covid and Non-Covid models of imageries and evaluated. The image denoising using DWT resulted in an SSIM value of 0.564 for covid images and 0.6935 for healthy lung images, NCC of 0.997 and 0.998 for covid and healthy lung images respectively and CC of 0.9794 and 0.99234 for covid and non-covid images respectively. Image denoising using BM3D the SSIM values are computed as 0.919 and 0.926 for covid and healthy lung images respectively, NCC of 0.9996 and 0.999689 for covid and healthy lung images respectively and CC of 0.99286 and 0.9967 for covid and healthy lung images respectively. It has been observed that the BM3D method provides a good performance compared to the DWT Technique for both covid and healthy lung images considering the performance metrics.

Keywords: Discrete Wavelet Transform (DWT), BM3D, CT scan Images, Covid-19, SSIM, NCC, CC, Image denoising.

1. INTRODUCTION

Corona Virus is an extremely transmissible disease and was first noticed in Wuhan, China in 2019.The virus has spread rapidly in a very short span of time and became a global pandemic[1].But recently the interest has inclined towards the prediction of the enduring effect of covid-19 effects in the individuals affected by COVID-19[2]. It is identified that, an individual after the covid-19 through current diagnosis system found negative is to be considered to be in the safe zone [3]. However, more intense studies performed globally on a limited number of patients show that the post COVID symptoms in various individuals have evidenced the presence of covid-19 and its impact of effecting individuals in a dreadful way [4]

2. LITERATURE SURVEY

There is a substantial amount of literature cited by the researchers in the research communal on the finding of covid-19 depending on the symptoms and its community infection rate [5]. Few interesting works such as detection of covid-19 from basic questions without in-vivo and in-vitro investigations [6]. The dataset features used by the learning model in the study emphasized on basic information such as gender and age (>60) followed by symptoms such as true/false statements on headache, sore throat, cough, fever and uneasiness in breathing followed by individual contact who is infected with covid-19 [7]. Another interesting work from [8], who classified the symptoms as most common, moderate and severe [9]. The most common symptoms are tiredness, cough and fever whereas moderate symptoms include diarrhoea, conjunctivitis, sore throat, loss of smell and taste and discoloration followed by severe symptoms such as uneasiness in breathing, chest pain and loss of movement [10]. The authors have used various algorithms such as support vector machine (SVM), Random Forest classifier (RFC), k-nearest neighbour (kNN), decision tree classifier and logistic regression. However, XGB classifiers predict the highest accuracy comparative to other available classifiers [11].
Most of the early publications on the machine learning practices for the estimate of COVID-19 are grounded on simple questionnaires, and an interesting question inline to this can be inferred from [12]. The type of the data

collected from the individual are breathing, diarrhoea, absence of smell, RT-PCR, fever, sore throat, dry cough, aches and pain followed by X-rays [13]. It stood conclusive that multi-layer perceptron and support vector machines have displayed excellent performance metrics [14]. In which accuracy and specificity are imperative in MLP and sensitivity and precision in SVM [15]. So, it is conclusive to us that no such algorithm is available that produces outstanding outcomes in specificity, accuracy, sensitivity and precision, hence suggesting a combination [16]. The works have been evaluated from basic questionnaires to the clinical data such as blood tests and have established immediate consideration in the global research standards. [17]

Few more interesting works from scientific literature on the development of machine knowledge representations to envisage the sternness of disease in covid-19 affected roles have been discussed in [18]. Alongside one more interesting paper on prediction of covid-19 for analysis, death and extremity in prognosis was reviewed with various machine learning methods such as Naïve Bayes, Decision trees, Adaboost, KNN that uses probabilistic classifier, ensemble algorithm to enhance the performance of the algorithm [19]. However though, few drawbacks such as there is a bias in existing dataset i.e., RT-PCR and CT scan [20]. With these drawbacks, an intuition from an author in their work [21] has reflected the importance of the database and availability of the database and their machine learning amenability was emphasized so that a proper algorithm can be carefully chosen for the type of the database [22]. They have also computed that less accuracy is attained when used with general deep learning, but though they have concluded that supervised learning is practiced well and accepted in a wider notion in the research community [23].

3. Data Preprocessing

The data pre-processing is done in four phases mentioned below:

1. Data cleaning 2. Data integration 3. Data transformation and 4. Data reduction.

1.Data cleaning: The data cleaning encompasses recognizing the mislaid values in the tuples, this can be reduced by choosing a suitable regression model to fit the data in the missing fields of the tuple [24]. Sometimes the data may involve lot of noise which can be reduced by a process referred to as binning and regression [25]. Binning is a process of smoothing the noise from the data to make it suitable for the next level of the program [26]. Recently, most of the literature uses clustering technique which is basically used if the data values are similar [27]. Sometimes the tuples may lie outside the data and these may render to inconsistence in the data and they are referred to as outliers [28].

2. Data integration: The persistence of the data integration is to merge the data present in multiple sources in a single data, which is the most important in our current phase of the project [29]. Sometimes data format types may be different, redundant attributes, detection and resolution may be present in the data as undesired elements [30]. This will be reduced by developing a suitable technique for machine learning compatibility [31].

1. Data transformation: Once the data cleaning and integration is performed, the quality of the data must be realized which require conversion of data to a form amenable for the machine learning algorithm [32]. This can be done in four ways referred to as generalization, normalization, attribute selection and aggregation [33]. Aggregation is one of the which can transform the structure of data depending on the type of the characteristics required [34].
2. Data reduction: Sometimes data will be too large and handling of the data could become difficult, to surmount this problem, data cube aggregation, dimensionality reduction, data compression, discretization, numerosity reduction and attribute subset selection followed by data quality assessment [35].
   This work considered the CT scan based COVID-19 dataset. CT scans are useful for tracking the course of the disease and determining the extent of lung involvement [36]. The distribution and amount of lung abnormalities visible on CT scans can reveal important details about the disease's severity [37]. Here, total 1252 images are found in COVID-19 class and total 1229 images are found in non-COVID-19 class in the downloaded dataset. From the following links, the dataset is collected [38].

Dataset links

https://www.kaggle.com/datasets/plameneduardo/sarscov2-ctscan-dataset?resource=download

Figure 1 shows the sample images from COVID-19 class and Figure 2 shows the sample images from non-COVID-19 class. Lung abnormalities linked with COVID-19, including consolidations, bilateral involvement, and ground-glass opacities (GGO), can be shown on CT scans as visible in Figure 1.These anomalies point to pneumonia, which is a typical sign of a serious COVID-19 infection [39].

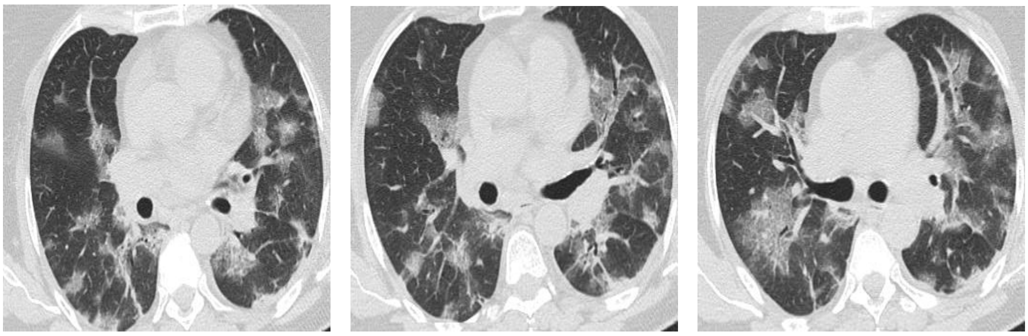

Figure 1: Sample images of COVID-19 class.

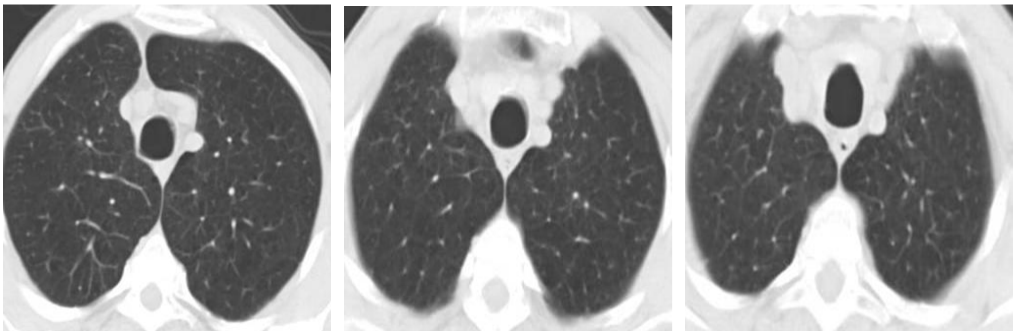

Figure 2: Sample images of non-COVID-19 class.

4. Existing methodology: Discrete Wavelet Transform (DWT)

The wavelet thresholding technique is being widely applied to the images with noise. The initial phase in this technique is discrete wavelet transform (DWT) [40]. DWT divides an image into sub bands through diverse coefficients: Low-Low, High-High, High-Low, and Low-High. Whereas the coefficient of sub-band of low frequency is termed estimate coefficients, the factors of high frequency, middle frequency sub bands are entitled detailed containing noise or significant signal features. Minor coefficients stand frequently triggered by noise, whereas big coefficients are produced by significant signal features. The wavelet thresholding procedure screens the small coefficients in the High-High, High-Low, and Low-High sub-bands by applying a threshold function. Soft-thresholding and hard-thresholding can be applied. While soft-thresholding technique puts the wavelet coefficients which are smaller amount than or equivalent to T as zero [26-30]. Too attained sieved imageries wavelet coefficients are cleaned and IDWT is applied.The filtered imageries were evaluated with quality metrics.

5. Proposed Methodology for Image Denoising of CT Images : Block-matching and 3D filtering (BM3D)

Block-matching and 3D filtering (BM3D) with hybrid wavelet transform is used as a preprocessing technique to revamp the eminence of CT imageries[19-25]. A 3D block-matching method called the BM3D algorithm is mostly cast-off to lessen the noise in the image as shown in Figure 3.

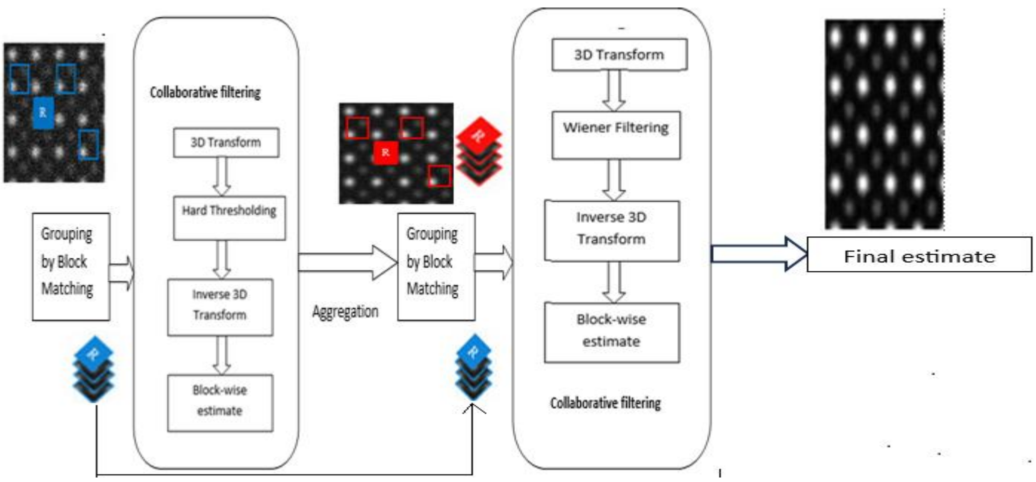

Figure 3: Block Matching Algorithm flowchart

Grouping of similar fragments is done in the first step based on similarities followed by collaborative filtering. A 3D transform is applied named Weiner filter, then the linear transform is reversed to replicate every sieved fragments. The next step is aggregation where an image is converted to 2D form and then collaborative filtering to get a final wiener estimate. [19-25].

5. RESULTS AND DISCUSSIONS

Images from the Kaggle dataset are taken and two types of noise namely poison noise, and salt-pepper noise which are mostly present in a CT Scan Scenario. These sources exhibit random photon fluctuation. The consequential representation is arbitrary in space and time. This clatter is otherwise a poison noise or quantum (photon) noise. Figure 4 illustrates the model output obtained post the preprocessing step of Imageries for Covid and Non-Covid.

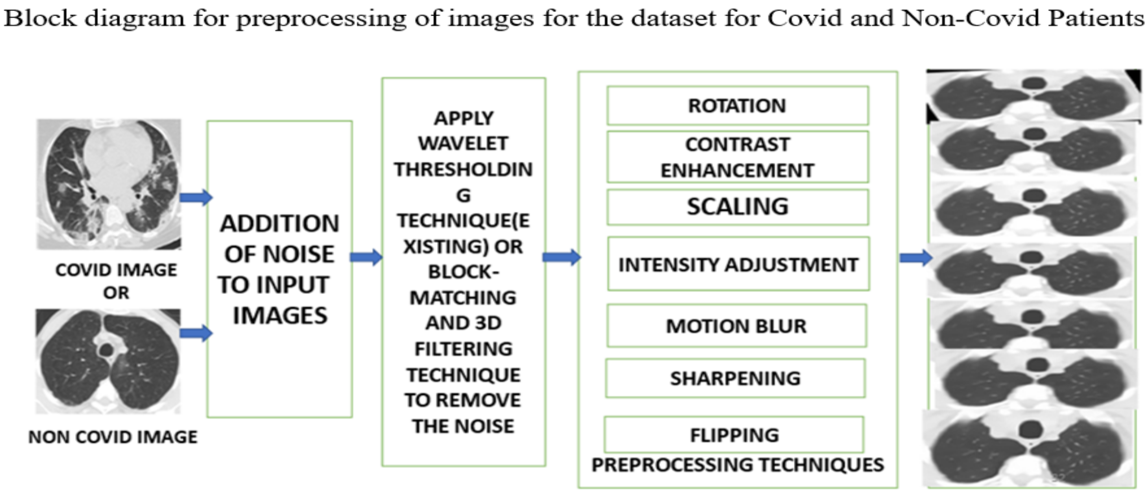

Figure 4: Methodology used for Preprocessing of Images for the dataset for Covid and Non-Covid Patients

This segment illustrates the comprehensive performance scrutiny of prevailing and anticipated methods. The performance is estimated for all the images in the dataset and analysis is done on various performance metrics.

Preprocessing performance metrics

The performance metrics analyzed in the work are Structural Similarity Index Metric (SSIM), Correlation Coefficient (CC) and Normalized Correlation Coefficient (NCC). Table 1, Table 2, Table 3 shows the SSIM, NCC, and CC metrics performance for COVID19 and non-COVID19 images.

Structural Similarity Index (SSIM).

SSIM is used as a metric to estimate the similarity among two specified images. A value closer to 1 indicates better image quality. The proposed BM3D procedure gives SSIM values nearby to 1and indicates that the method can be used for objective analysis of the disease progression effectively as indicated in Table 1. A value closer to 1 indicates that the method has good denoising and better image quality.

Table 1: SSIM Performance assessment for Covid and Non-Covid Images

Preprocessing method	Covid19		Non-Covid19	
	Wavelet thresholding technique	BM3D Algorithm	Wavelet thresholding technique	BM3D Algorithm
Noise added to the image	0.564695	0.838337	0.693541	0.861203
Rotation	0.232125	0.745489	0.400267	0.839128
Scaling	0.564695	0.843516	0.693541	0.909002
Contrast Contrast adjustment	0.000159	0.840268	0.000569	0.909821
Intensity adjustment	0.000155	0.840268	0.000564	0.909821
Motion Blurring	0.564695	0.696439	0.693541	0.855923
Sharpening	0.564695	0.919483	0.693541	0.926469
Flipping	0.224782	0.840268	0.396578	0.909821

Normalized correlation coefficient (NCC)

The Normalised Cross-Correlation (NCC) metric is in fact a widely used way to gauge image similarity. Based on the pixel intensities of the two photos, it measures how similar the two are. A higher score shows a stronger resemblance amongst the photos. The NCC value lies from 0 to 1.

NCC evaluates the normalised covariance between two pictures while accounting for the pixel's mean intensity values. NCC removes the influence of the images' overall intensity levels and concentrates on their relative similarities by normalising the covariance.

When the NCC value is close to 1, it indicates that the two photos are quite similar to one another. This shows that the photos' pixel intensities are closely connected and display comparable patterns or structures. As opposed to that, an NCC value nearer to 0 recommends a lower comparison, inferring that the pixel intensities in the images are fewer correlated or have diverse patterns. It has been emphasized from Table 2 that the projected BM3D technique puts up NCC values near to 1.A higher value of NCC indicates that there is perfect correlation between the images. The metric can be used to provide insights into disease severity and progression over time.

Table 2: NCC Performance assessment for Covid and Non-Covid Images

Preprocessing method	Covid19		Non-Covid19	
	Wavelet thresholding technique	BM3D Algorithm	Wavelet thresholding technique	BM3D Algorithm
Noise added to the image	0.997536	0.999139	0.998409	0.999221
Rotation	0.918285	0.95758	0.882636	0.929544
Scaling	0.997536	0.99959	0.998409	0.999586
Contrast adjustment	0.160657	0.999623	0.232176	0.999689
Intensity adjustment	0.153992	0.999623	0.201359	0.999689
Motion Blurring	0.997536	0.997621	0.998409	0.99874
Sharpening	0.997536	0.999285	0.998409	0.999586
Flipping	0.930983	0.999623	0.933211	0.999689

Correlation Coefficient (CC)

The degree and direction of the linear link between two variables are measured by the correlation coefficient. Its value is always in the -1 to +1 range.

A direct or positive association between the variables is indicated if the correlation coefficient is positive (nearer to +1). In other words, the tendency is for the other variable to increase as one variable does. This positive correlation implies that the variables have a comparable and identical relationship.

Conversely, a negative or inverse association between the variables is indicated if the correlation coefficient is negative (closer to -1). This implies that the tendency is for the other variable to decrease as the first variable rises. The absence of a positive correlation indicates that the variables are unrelated or have an inverse relationship.

Table 3 shows that the projected BM3D method gives CC standards which are positive and close to 1. It can give insights into the percentage of lungs affected by the disease progression over time.

Table 3: CC Performance assessment for Covid and Non-Covid Images

Preprocessing method	Covid19		Non-Covid19	
	Wavelet thresholding technique	BM3D Algorithm	Wavelet thresholding technique	BM3D Algorithm
Noise added to the image	0.979425	0.99286	0.993234	0.996678
Rotation	0.481654	0.742125	0.556145	0.736481
Scaling	0.979425	0.996588	0.993234	0.998237
Contrast adjustment	0.149685	0.99686	0.233814	0.998679
Intensity adjustment	0.14524	0.99686	0.203357	0.998679
Motion Blurring	0.979425	0.980252	0.993234	0.994652
Sharpening	0.423499	0.99686	0.715684	0.998679
Flipping	0.423499	0.99686	0.715684	0.998679

CONCLUSION

Covid Images are taken from the dataset and salt and pepper noise has been applied. Wavelet Thresholding Technique was applied for denoising. The projected BM3D technique caused in greater preprocessing performance for the metrics SSIM, CC, NCC. Further, the effectuation of anticipated technique is enhanced for “Noisy, Rotate, Scaling, Contrast enhancement, Intensity change, Motion Blur, Sharpening, and Flipping” cases as associated to prevailing technique for every evaluation parameter.In order to better educate patient management and treatment decisions, performance metrics analysis in COVID-19 CT scans can assist clarify the relationship between radiological results and numerous clinical, laboratory, and diagnostic factors. Any analysis method's drawbacks and subtleties must be taken into account, and the results must be interpreted in light of clinical observations and other pertinent data. Additionally, when using image analysis techniques in medical imaging contexts, validation and domain-specific issues are critical.

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