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Development of a Multi-modal Severity Prediction System for Covid-19 using Machine Learning Algorithms

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Abstract: Medical systems all over the world have been devastated by the covid19 pandemic. Even abundant and wealthy countries have struggled a lot. As of August, 2022, number of corona virus cases has been reached to almost 588 million worldwide reported to WHO. With automation at the level of covid19 severity prediction can improve healthcare delivery in parts of the world where access to skilled experts is limited. It can also help in resource management and reducing mortality rate.

Method: In this research, the researchers designed and developed a novel multimodal framework for covid19 severity prediction with a high precision capacity including decisions from medical imaging and clinical factors including patient details, co morbidities and blood results. The researchers explored oversampling methods SMOTE and ROC with SVM, Decision Tree, Random Forest and ANN classifiers for predicting severity using clinical factors. Image enhancement methods gamma correction and AHE explored with ChexNet model for severity prediction through X-ray images. Performance of the predictions has been evaluated using accuracy, precision, sensitivity, and F1-score.

Results: The researchers achieved superior prediction using RF classifier with SMOTE method for text dataset with accuracy of 96%. For X-ray image dataset ChexNet with AHE achieved 87% accuracy. Infection severity inversely proportional to clinical factors LYP, LY,MOP,CA, ALB and ALG where as it is directly proportional to AST, ALT,DD,CRP,LDH,BUN,CR,MCH,GLU,TBIL and WBC.
In the future, performance of the image model may be improved by concatenating multi scale features from different layers of CNN to increase representation power of the CNN model. Again channel attention may be beneficial to improve model performance.

Keywords: *Covid-19 diagnosis, Severity prediction, Machine learning, CNN, Deep learning, Multi-modal*

1. Introduction

The alternative which can overcome limitations of medical resources in epidemic situation is predictive model using machine learning for covid19 diagnosis. Models based on machine learning can gain understanding of different patterns found in the blood test parameters which is difficult to analyze manually. Highly trained machine learning models can detect ambiguities in chest radiographic images that are not noticeable by experts. Once learned a computerized model, it can predict severity of infection very fast. Model may be deployed to assist medical staff to validate their decisions. It may also be helpful to defeat the problem of lacking specialized experts in remote places.

1.1. Related Work

Researchers applied efforts to develop machine learning approaches for covid19 diagnosis. Efforts applied can be divided into two categories: diagnostic models using chest radiology images and diagnostic models through patient details and clinical features. The classification model of COVID-19 chest CT images and pneumonia chest CT images has been developed [4]. Different models based on pre trained convolution neural networks have been explored to detect of corona virus positive patient using chest X-ray images [5]. The concept of transfer learning explored to classify chest X-Ray image into normal, Covid-19 or Pneumonia [2].

A fusion model developed by the authors using text and CT image data [6]. Random Forests (RF) classifier used for textual model and GoogleNet deep learning network used as image model. Text data includes symptoms, risk factors, medical analysis extracted from medical cases and image data from lung CT images.

A CNN model pre-trained on large and non-COVID-19 chest X-ray image dataset is used to extract features from COVID-19 images and severity score from extracted features is predicted [7]. The author applied the concept of transfer learning to predict positivity of COVID 19 through chest X-Ray images [8]. They used different architectures of convolution neural networks (CNNs) which were trained on ImageNet dataset. Pre trained CNNS are modified to extract X-ray image features. Then basic machine learning methods, like multilayer perceptron, support vector machine, k-Nearest Neighbor, Bayes, and Random Forest applied for classification.

COVIDGR dataset and COVID-SDNet approach to predict severity of COVID-19 infection based on chest X-Ray images has been proposed in [9]. The severity of disease infection is classified as mild, moderate and severe. The DarkNet model

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wasmodified by the author in [10] and used as a classifier for COVID19 or normal or pneumonia x-ray images. Modified model named as DarkCovidNet. The authors in [11] provided the resource labeled as integrative CT images and CFs for COVID-19 (iCTCF) which includes CT images and clinical factors of patients. They also proposed a fusion model named HUST-19 to predict mortality by integrating CT image result and results from clinical parameters.

Studies reveal that classification of several lung infections through only radiology is extremely difficult without paying attention to other medical parameters. A system including features from different modalities such as x-ray images, patient details and clinical parameters will be utilized to improve diagnosis system even for asymptotic positive cases also. Studies reveal that most efforts applied to predict covid19 positivity. Predicting infection severity can be helpful in resource management and reducing mortality.

The main interest of the study is to design and develop multimodal severity prediction model for COVID-19 through parameters like patient details, co morbidities, blood reports and X-ray images. Upcoming sections include datasets and methods, results of experiments, discussion, conclusion and future scope.

2. Datasets and Methods

Covid-19 severity prediction model with multi modal inputs developed using machine learning. This section includes datasets used to develop model, proposed system flowchart, approaches for text and image model, and performance evaluation metrics.

2.1. Dataset

Two datasets used to develop prediction models. Image dataset COVIDGR 1.0 contains chest X-ray images and Text dataset iCTCF contains clinical factors. Details regarding the datasets described in this section.

2.1.1. Image dataset

COVIDGR 1.0 dataset is freely available at https://dasci.es/es/transferencia/open-data/covidgr/. Dataset includes two classes, positive and negative with 452 samples in each class. Severity level for positive sample defined using RALE (Radiographic Assessment of Lung Edema) score as shown in Figure1. All the images were obtained from the same equipment. High quality Posterior Anterior (PA) view is considered. Number of samples for each category mentioned in Table1

Table 1. Number of images for different severity class [9]

Class	*#Images*	*Images per severity level*
Negative	426	
COVID-19	426	Mild:100 Moderate:171 Severe:79

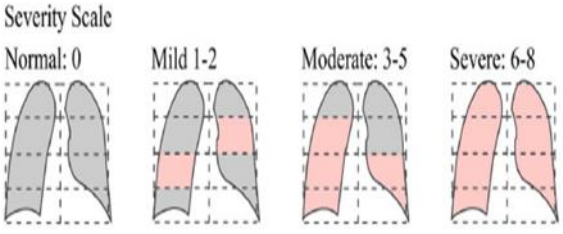

Fig1. Severity RALE Score [9]

2.1.2. Text Dataset

iCTCF is freely available for academic research at http://ictcf.biocuckoo.cn.

The CF data includes basic information, underlying diseases, routine blood test and inflammation test. Data provided of patients with different levels of infection like mild, regular, severe and critically ill. The author collected 23 mild, 100 moderate and 100 severe samples from the dataset. Description of blood test parameters is shown in Table2.

Table 2. Clinical Features

Clinical feature	*Abbreviation*	*Value*	*Normal range*
Alanine aminotransferase	ALT	63.00 ↑	5-40 U/L
Aspartate aminotransferase	AST	44.00 ↑	8-40 U/L
Urea nitrogen	BUN	6.96	2.9-8.2 mmol/L
Creatinine	CREA	74.3	44.0-133.0 μmol/L
C-reactive protein	CRP	15.40 ↑	<8.00 mg/L
D-Dimer	DD	1.26 ↑	<0.5 mg/L FEU
Eosinophil percent	EOP	3.1	0.4-8.0 %
Glucose	GLU	4.82	3.90-6.10 mmol/L
Hematocrit	HCT	35.80 ↓	40-50 %
Hemoglobin	HGB	123.00 ↓	130-175 g/L
Lymphocyte percent	LYP	41.2	20-50 %
Mean corpuscular hemoglobin	MCH	31.2	27-34 pg
Monocyte percent	MOP	8.7	3-10 %
Platelet count	PLT	304	125-350 G/L
Coefficient variation of red cell volume distribution width	RDWCV	12.5	<14.5 %
Total bilirubin	TBIL	9.8	5.1-19.0 μmol/L
White blood cell	WBC	2.42 ↓	3.5-9.5 G/L

2.2. System Flowchart

In this section, we describe severity prediction system including details about image model and text model. Overall system design is presented in Figure2. X- Ray images and blood test results along with patient's details are input to the system. Image model takes X-Ray image and predicts severity class (Yhat1) with probability Yprob1. Text model takes blood test parameters of COVID 19 patients as input and predicts severity class (Yhat2) with probability Yprob2. If prediction of both models is same (Yhat1=Yhat2), it will be final prediction by the system otherwise expert advice is recommended.

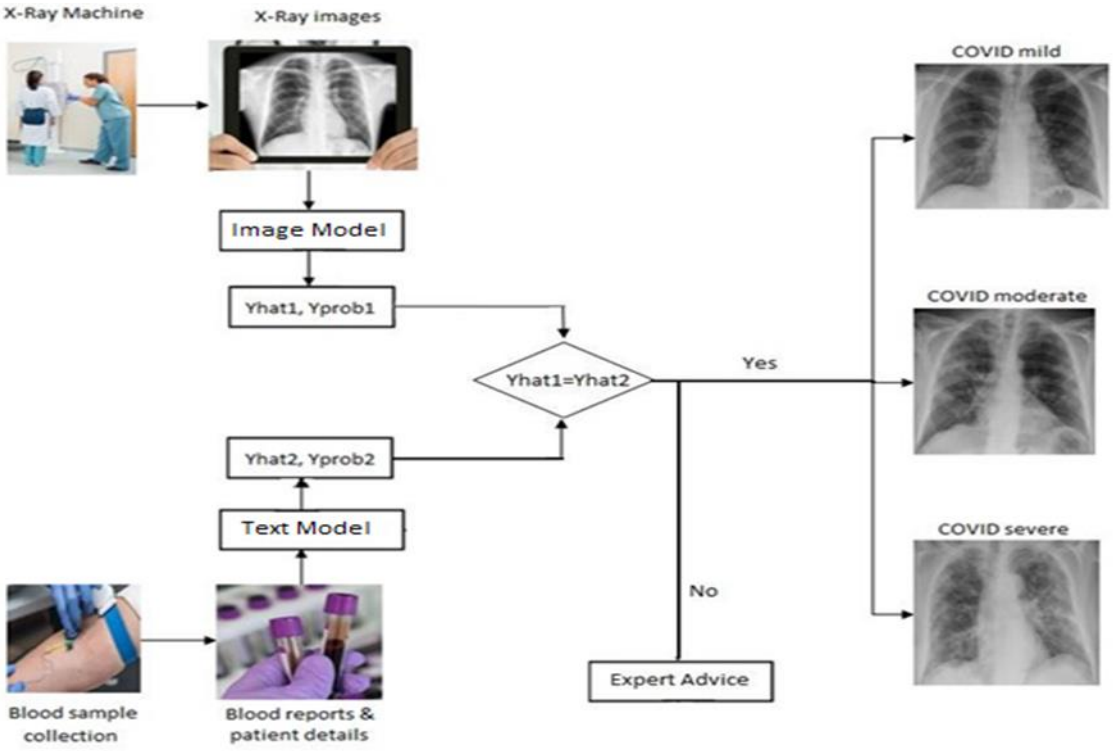

Fig 2. System Flowchart

2.2.1. Methodology for image model

Image model has mainly two stages, Pre-processing and classifier as shown in Figure3. ROI based cropping; image augmentation and image enhancement are applied as pre-processing stage. X-ray images include extra information depending upon X-ray equipment, position and size of the patient. Lungs are cropped from X-ray images. Model learns well if sufficient data is available. Image augmentation applied to increase samples and to make dataset balanced. Image enhancement is the approach to improve the quality and content of the images. We explored adaptive histogram equalization (AHE) and gamma correction for image enhancement which basically improves overall brightness of the image [13][14][15]. Each image rescaled to [224,224] and normalized between 0 to1.

We have used ChexNet initialized with pre trained weights as a classifier. ChexNet is Densenet121 architecture retrained on large chest X-ray dataset[12]. Transfer learning approach selected due to limited dataset and considering problem similarity, ChexNet has been chosen. To adapt model for our problem, we removed last layer from net and added four dense layers with 512, 128, 64 and 3 neurons as shown in Figure4. ReLu activation used for dense layer, except last one for which softmax activation applied.

2.2.2 Methodology for Text Classifier

Text model developed with three main stages, pre-processing, oversampling and classification as shown in Figure5. Pre-processing is a crucial step before training the model. Null values in the dataset are replaced by the most frequent value in the column with same class samples. Label encoding used for categorical values to define each category with numerical values. Continuous values are scaled using min-max scaling which is beneficial for fast training of model and reducing computations. Clinical factors are analyzed to find most relevant factors for predicting infection severity.

A issue with imbalance classification is learning the decision boundary of the model precisely due to few samples of the minority category. Samples in the minority class are increased by ROS and SMOTE. ROS (Random oversampling) just increases the size of the minority samples by repetition of the original samples. It does not cause any increase in the variety of training examples [17]. Oversampling using SMOTE (Synthetic Minority Oversampling Technique) increases variations in samples instead of just increasing the size of the training samples [16]. From minority category a random sample is first selected. Nearest neighbours for the selected sample are retrieved from which one neighbour is chosen randomly. A synthetic sample is created randomly between the two samples in the feature space.

Mostly used ML classifiers, decision tree, SVM, random forest and ANN implemented using original and balanced datasets and performance evaluated on validation dataset.

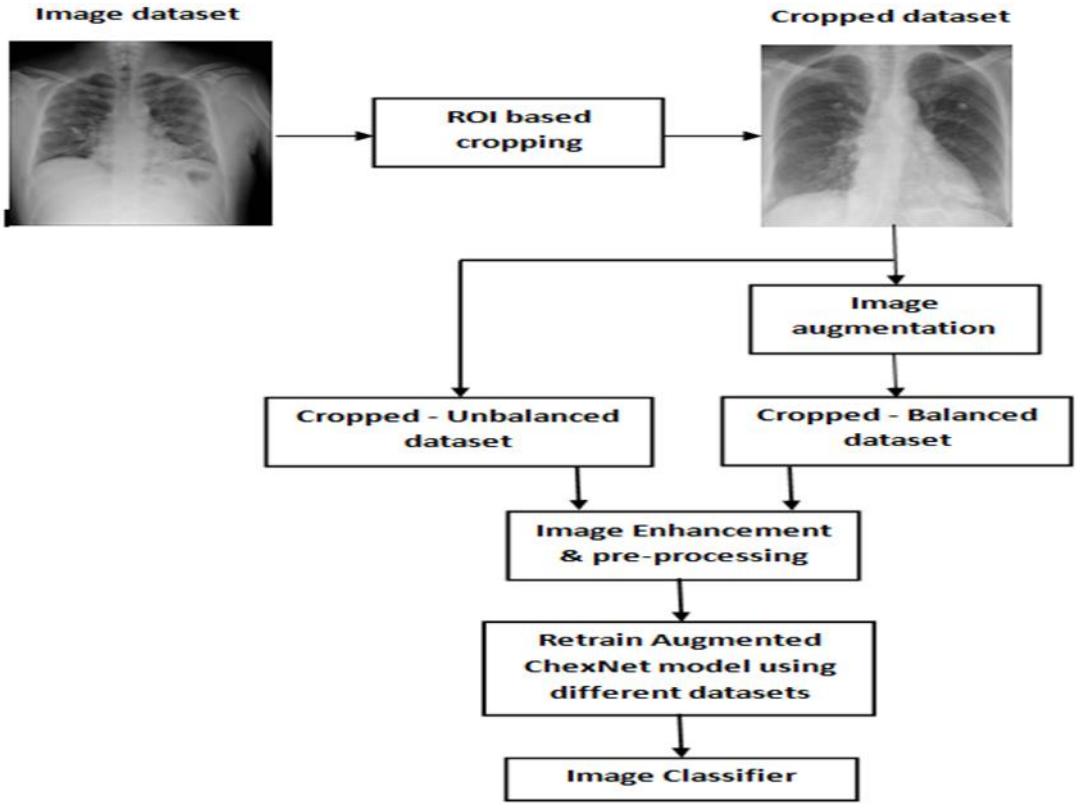

Fig3. Image Model

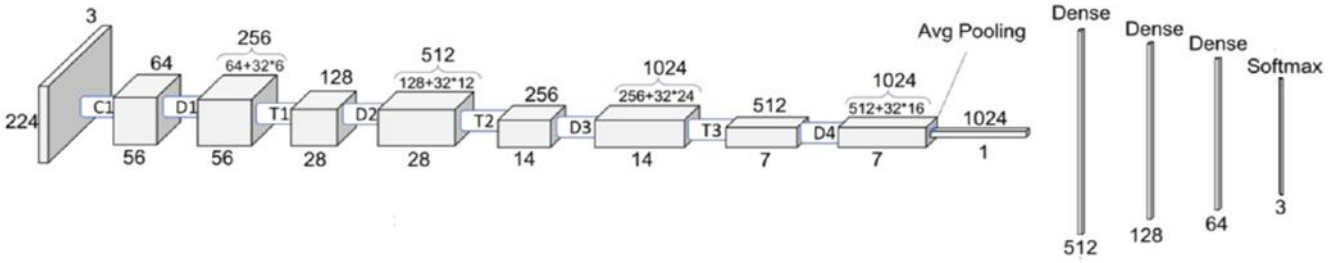

Fig4. Augmented ChexNet Architecture [12]

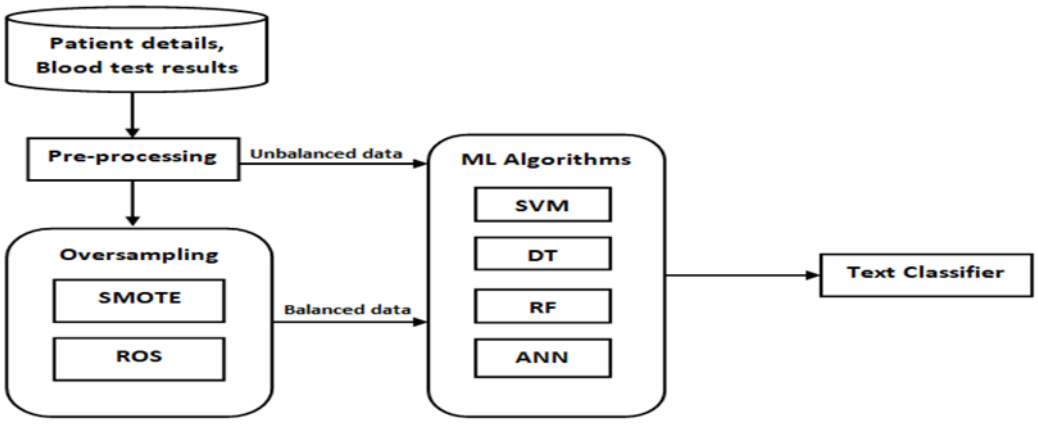

Fig 5. Text Classifier

2.3. Performance Evaluation Metrics

The researchers used four metrics to evaluate model performance: sensitivity, precision, accuracy and F1 score. Sensitivity or recall is the measure of true positive perditions by the model from actual positive cases in inputs. Precision defines actual positive predictions from total positive predictions done by the model. Accuracy measures correct predictions of the model out of total samples. F1 Score is the average of the precision and sensitivity [18][19]. Good prediction system has high F1 score value balancing between precision and sensitivity scores of predictions. F1 score value ranges between 0 to1. Followings are the equations of performance metrics [20].

$Sensitivity = TP/(TP + FN)$

$Precision = TP/(TP + FP))$

$$Accuracy = (TP + TN)/(TP + FP + FN + TN)$$
$$F1\ Score\ = 2 * (Recall\ *\ Precision)\ /\ (Recall + Precision)$$

3. Experimental Results and Discussion

Extensive experiments are conducted to develop proposed models.

For image model, ChexNet model retrained on image dataset with six variations like original dataset, original-AHE, original gamma, balanced dataset, balanced-AHE and balanced-gamma. Performance of each trained model is evaluated on validation dataset and model performing best is selected as image model. For text model, four classifiers trained on two datasets, original and over sampled (balanced) resulting eight classifiers in total. A classifier predicting with high accuracy on validation data is selected as text model.

3.1. Performance of image model

Table-3 represents validation accuracy of ChexNet model on original and balanced datasets with different image enhancement approach. Accuracy score of model trained on unbalanced dataset(original, AHE, gamma) is 71.9, 63.5 and 63.2 respectively. Accuracy score of model trained on Balanced dataset(original, AHE, gamma) is 80,87 and 84 respectively. Accuracy of the model also plotted in Figure6. From table it is clear that using AHE technique with balanced dataset, highest average accuracy 87 is achieved. Precision, recall and F1-score values of the model trained on different datasets also represented in Table-4. Values of F1 score of the model trained on balanced dataset with AHE for mild, moderate and severe category are 81%, 82% and 98%, respectively.

Table3. Accuracy of ChexNet Model with Different Datasets

	Unbalanced dataset				***Balanced dataset***			
	Original	***AHE***	***Gamma***	***support***	***Original***	***AHE***	***Gamma***	***support***
Mild	0.5405	0.5263	0.5789	19	0.8596	0.7895	0.7018	57
Moderate	0.7422	0.8788	0.8182	33	0.6316	0.8596	0.9123	57
Severe	0.8772	0.5	0.5	14	0.9298	0.9649	0.9123	57
Average	0.719974	0.635035	0.632376	66	0.807018	0.871345	0.842105	171

Table4. Performance Comparison of ChexNet Model with Different Datasets

Unbalanced dataset										
	Original			***Gamma Correction***			***AHE***			
	precision	***recall***	***f1-score***	***precision***	***recall***	***f1-score***	***precision***	***recall***	***f1-score***	***Support***
Mild	0.7	0.54	0.61	0.73	0.58	0.65	0.77	0.53	0.62	19
Moderate	0.71	0.74	0.73	0.64	0.82	0.72	0.64	0.88	0.74	33
Severe	0.74	0.88	0.8	0.78	0.5	0.61	0.88	0.5	0.64	14
Balanced dataset										
	Original			***Gamma Correction***			***AHE***			
	precision	***recall***	***f1-score***	***precision***	***recall***	***f1-score***	***precision***	***recall***	***f1-score***	***support***
Mild	0.66	0.86	0.75	0.87	0.7	0.78	0.83	0.79	0.81	57
Moderate	0.82	0.63	0.71	0.71	0.91	0.8	0.79	0.86	0.82	57
Severe	1	0.93	0.96	1	0.91	0.95	1	0.96	0.98	57

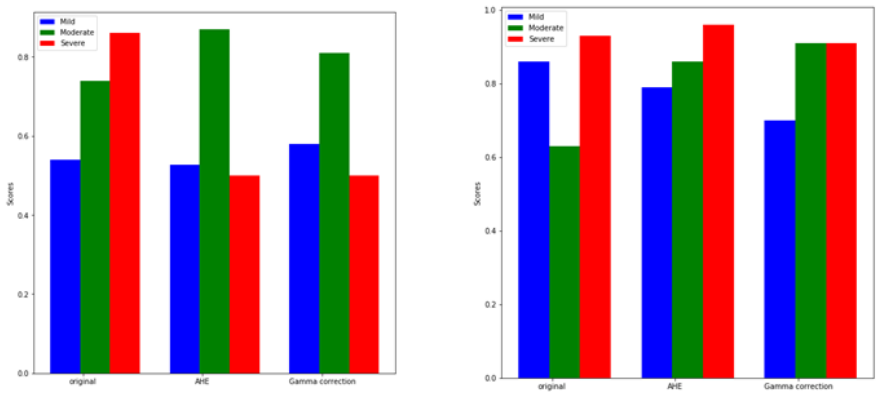

Fig 6. Accuracy plot 1. Unbalanced dataset 2. Balanced augmented dataset

3.2. Clinical factors analysis

Values of clinical factors with respect to severity classes are plotted and analyzed using box plot. Values of LYP, LY,MOP,CA, ALB and ALG decrease as infection increases as shown in figure 8 whereas values of AST, ALT,DD,CRP,LDH,BUN,CR,MCH,GLU,TBIL and WBC increase as infection increases as presented in Figure7.

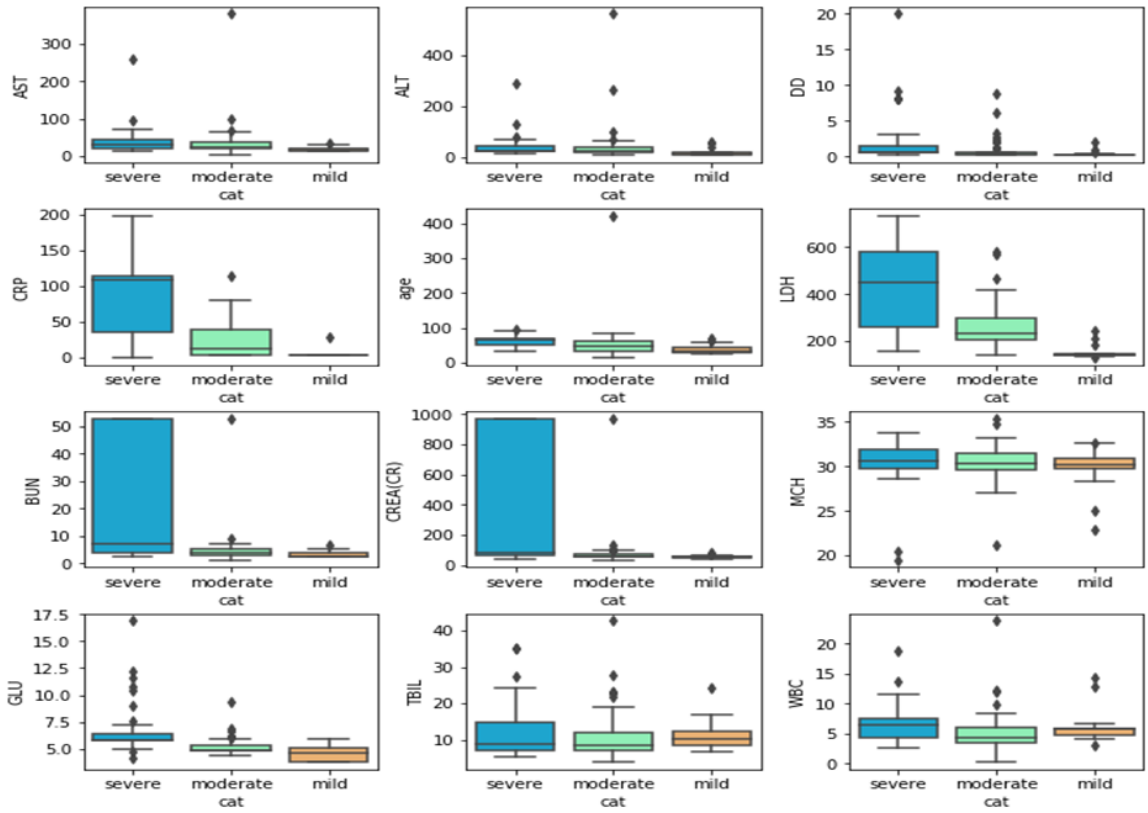

Fig7. CFs with Increase in Values as Infection Severity Increases

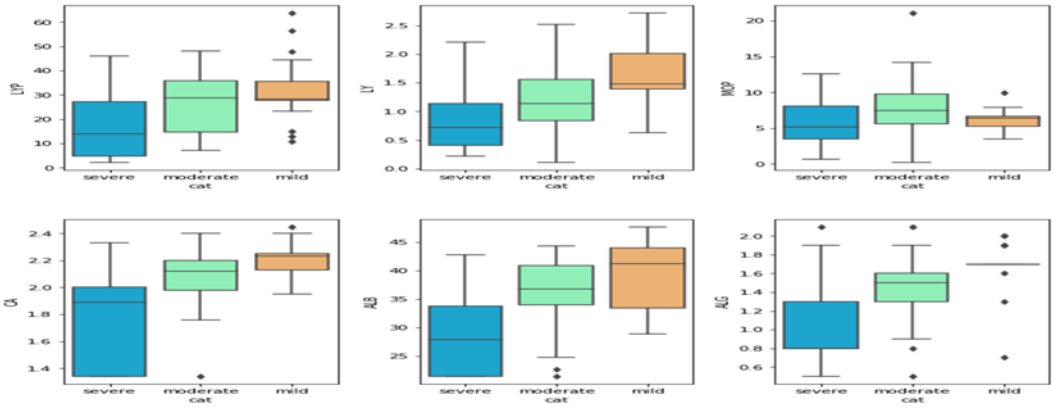

Fig8. CFs with Decrease in Values as Infection Severity Increases

3.3. Performance of Text Model

Table-5 represents validation accuracy of ML Classifiers with oversampling techniques (ROS, SMOTE). It is observed from table that instead of classifier trained on original dataset, classifier trained on balanced dataset with oversampling performed well. From table it is clear that Using RF classifier with SMOTE achieved highest accuracy 96%. Accuracy plot of all classifiers is shown in Figure10. Classification report of RF classifier with SMOTE approach is also shown in Figure9. F1 score values for mild, moderate and severe class are 100,95 and 95, respectively.

Table 5. Accuracy of ML Classifiers with ROS and SMOTE Oversampling

	Random Forest	***ANN***	***SVM1***	***DT***
Unbalanced	0.772727273	0.545455	0.590909	0.681818
ROC	0.888888889	0.777778	0.703704	0.814815
SMOTE	0.962962963	0.814815	0.666667	0.851852

RF smote report

	precision	recall	f1-score	support
mild	1.00	1.00	1.00	8
moderate	1.00	0.90	0.95	10
severe	0.90	1.00	0.95	9
accuracy			0.96	27

Fig9. Classification Report

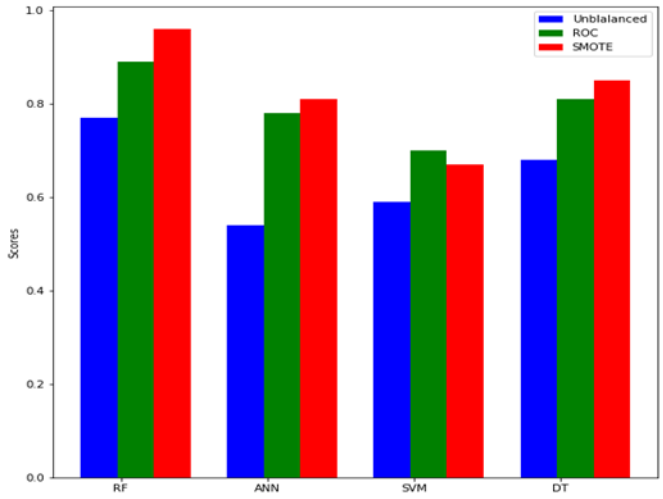

Fig10. Accuracy plot of ML Classifiers

3.4. Test Results of proposed models on GMERS Hospital dataset

The researchers have collected blood reports and x-ray images of 10 patients admitted to GMERS hospital, Gandhinagar. Classification result on collected dataset by developed models shown in table. Out of 10 samples, 6 samples predicted correctly by both inputs (Image and blood report). 2 samples incorrectly predicted by X-ray images (case 5 and case 7) out of that case 7 correctly predicted by blood report. 3 samples incorrectly predicted by blood reports (case 4,5 and 6) out of that case 4 and case 6 correctly predicted by x-ray images. Collectively only one case incorrectly predicted by both models.

Table 6. Test results on GMERS Hospital dataset

Case. No	***Patient Name***	***Expert Opinion***	***Prediction by model***		***Final Decision***
			Text	***Image***	
1	Liliben	Moderate	Moderate	Moderate	Moderate
2	Pujiben	Mild	Mild	Mild	Mild
3	Dalsiben	Moderate	Moderate	Moderate	Moderate
4	Ramanbhai	Mild	Moderate	Mild	Expert Advice
5	Ranjeetbhai	Severe	Moderate	Mild	Expert Advice
6	Devendrabhai	Mild	Moderate	Mild	Expert Advice
7	Meeraben	Moderate	Moderate	Mild	Expert Advice
8	Prafullaben	Severe	Severe	Severe	Severe
9	Vishnubhai	Moderate	Moderate	Moderate	Moderate
10	Kananben	Moderate	Moderate	Moderate	Moderate

4. Conclusion

Due to limited medical resources in pandemic, an automatic prediction system can be a fast alternative to diagnosis methods to control disease expansion, mortality and resource management. We designed a novel approach for covid19 diagnosis with a high clinical value including decisions from multi modal inputs and predicting infection severity instead of COVID19 positivity. The researchers got superior performance using RF classifier with SMOTE method for text dataset with accuracy of 96%. For X-ray image dataset ChexNet with AHE achieved 87% accuracy.

The developed model does not replace existing diagnosis methods but reduces urgent need for experts in the parts of the worlds where access to skilled experts is limited and thus improves healthcare delivery.

Increasing samples of minority class by oversampling methods helps to gain the classification results. Instead of training a CNN model directly on available dataset, pre processing of images like cropping of interested region from image and image enhancement before training a model gains the performance of CNN model.

Also image augmentation can be beneficial to increase images of minority class and thus high performance.

5. Future Scope

In the future study, other CNN models can be explored to improve classification results. Performance of the CNN model may be improved by concatenating multi scale features from different layers of CNN to increase representation power of the CNN model. Again channel attention may be beneficial to improve model performance.

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