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Performance Comparison of various T-Norms with Choquet integral inFuzzy Logic using Covid-19 Chest X-Ray Data

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Abstract

Covid-19 declared by WHO as a global pandemic leading to millions of deaths. In this paper we are integrating various t-norms in fuzzy logic and want to see which t-norm will perform the best. Here the ensemble model is used to distinguish chest X ray images as Covid infected, Pneumonia infected and Normal patients. Transfer learning technique is used to train four very powerful CNN's namely Vgg16, Restnet50, InceptionnetV3 and Densenet121.These pretrained CNN models are feature extracted and then used as classifiers for the chest X- ray images. After that the prediction results of the individual models are aggregated using Choquet integral with various t-norms based fuzzy measure like Lukaseiweiz , Hemaecher and Nilpotent and the final labels are predicted which are more strong than the prediction of individual models. In order to evaluate the proposed model chest x ray images from public repositories like IEEE and Kaggle are used. The final prediction results are better than the individual results of the base CNN models.

Keywords: choquet integral, t-norms, fuzzy measures, lukaseiweiz, hemaecher, nilpotent, ensemble methods.

1. Introduction

COVID-19 is a respiratory system related disease which is very contagious and hence spreads very fast. It is recognized as a global pandemic which resulted in millions of deaths. The specialty of COVID-19 is it has very long incubation period. A person may appear healthy but in fact can be a asymptotic carrier of this virus. In spite of the vaccination drive new variants continue to emerge which becomes a challenge to stop the propagation of this disease. So, it is now the need of the hour to quickly diagnose this disease and isolate the infected persons to prevent the chance of healthy people getting infected.

As deep learning is a popular technique for image processing and more so Convolutional Neural Networks in deep learning are very effective tools for computer vision related problems. CNN's can be used to process Chest X-ray images as well as CT images. This study is solely based on analyzing Chest X-ray images to detect the infected persons. Chest X-ray are less expensive than CT scans. So the aim of this paper is to develop a method which is inexpensiveas well as accurate.

Majority of the research studies has used CNN for the image classification purpose as the features are extracted automatically instead of manually as in the case of classifiers like decision trees, KNN etc. The advanced CNN's like Resnet[8] and its variants, VGG and its variants can do this feature extraction more accurately as they are pretrained on ImageNet datasets which has millionsof images of different types belonging to almost nearly 20000 classes.

In this proposed paper as the dataset is small it cannot be used to train the existing CNNs from scratch so a technique known as transfer learning is used to compensate for the small dataset size. In transfer learning a technique called as feature extraction is used to extract the features from the chest X-ray images.

The output layer of the CNN is reshaped to suit the classification task at hand. In order to make the predictions very accurate ensemble technique is being applied. In the area of ensemble modeling instead of using the basic ensemble techniques like weighted average, majority voting it was decided to use fuzzy integrals with fuzzy membership functions for aggregating the individual predictions. Another reason for applying ensemble technique is to reduce the variation in the prediction results of individual models. The advantage of fuzzy integrals as aggregation operators is used to add dynamism when ensembling the base classifiers. Here the four CNN's namely VGG16, Resnet50, Densenet121[9] and Inceptionnet V3 are aggregated using Choquet integral with various t-norms fuzzy measure like Lukaseiweiz, Hemaechar and Nilpotent.

2. Related Work

The fast spread of COVID-19 globally and its disastrous effects on the healthand life of people all over the world made it an important research area for many researchers in the area of image processing and artificial intelligence.

Sherwin et al [1] used four popular pretrained CNN's like Resnet18[8], Restnet50[8], Squeezenet[10] and Densenet121[9] applied transfer learning to account for the small dataset size and proved that Squeezenet[10] and Resnet50[8] gave better accuracy in predicting covid -19 from the chest X-ray images. Weiqiu et al [2] used hybrid ensemble technique to differentiate between Covid-19 and viral pneumonia from chest X-ray images. In this paper the author has used pretrained Alexnet for feature extraction which were passedto RelieFf algorithm to select the best features then the selected n best features were used to train the SVM classifier for final prediction. Amit Kumar et al[3] combined three state of the art pretrained models like DenseNet201, Resnet50V2[8] and Inceptionnetv3.They were trained individually and later the predictions were aggregated using Weighted average ensemble technique to predict the class labels. Mohamed et al[4] used two ensemble method stackingand weighted average to combine the results of three pretrained CNN models(VGG19,Densenet201[9],Resnet50[8]) to analyse CT images for covid-19 detection. Rohit et al[5] applied Fuzzy rank-based fusion of CNN using Gompertz function for screening Covid-19 CT scan images.

It can be observed that ensemble techniques can be used to combine the prediction results from various classifiers to improve the final classification result. The problem with classical ensemble technique is that they are not dynamic. In this case Choquet fuzzy integral with t-norm based fuzzy measure is used to ensemble the CNN's (VGG16,Resnet50[8],Densenet121[9] and InceptionnetV3).The validation accuracies of individual CNN's are combined for more accurate prediction. The proposed technique is unique as it is not used any of the existing research.

3. Proposed System

In this paper fuzzy classifier is used as an ensemble technique. Various t-normbased fuzzy measures are combined with Choquet integral to form various combinations of fuzzy classifiers. Here there are three combinations generated by combing three different t-norms with Choquet Fuzzy Integral as shown in Figure 1

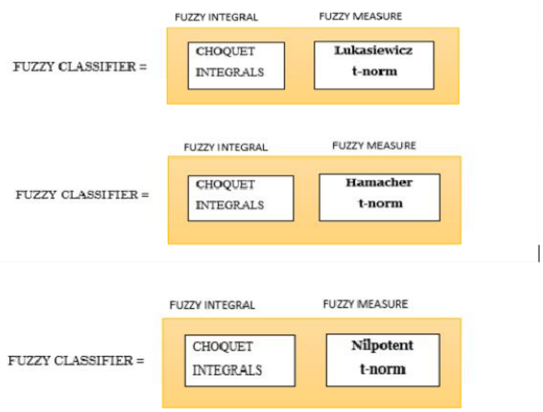


Figure 1 Different Combinations of Fuzzy

These combinations are used to combine prediction results from four different pretrained CNNs on ImageNet dataset after reshaping the output layers to suit the specific classification task. The architecture of proposed system is as shownin Figure 2

Definition of T-norms

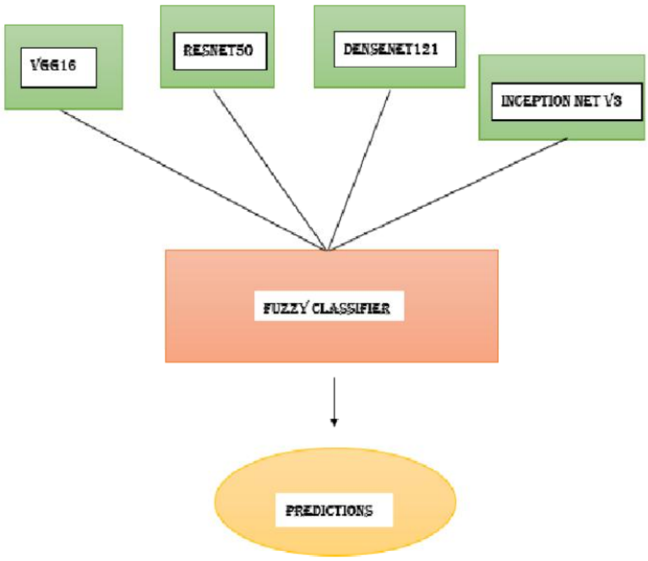
- A triangular norm (t-norm) is a binary operation T on the interval [0,1] satisfying the following conditions:

➢ T (x, y)=T(y , x) (Commutative)

➢ T(x , T(y , z)) = T(T(x , y),z) (Associative)

➢ y<=z => T(x , y)<= T(x , z) (Monotonicity)

➢ T(x, 1) = x (neutral element 1) [7]



High Level Architecture Diagram

Figure 2 High Level Architecture of Proposed System

Examples of T-norms

- **Lukasiewiez t-norm**

Formula: T(x , y)= max(x + y - 1 , 0)

∟ The only t-norms which are rational functions are the **Hemaecher**

t-norms defined for all *r*>0 by

Formula : for r > 0

T(x , y) = x y / r+(1-r)(x + y- x y)for r = 0

T(x , y) = x y/ (x + y – x y)

∟ The idempotents of t-norms T are those satisfying T(x, x)=x. Continuous Archimedean t-norms which are not strict are called **nilpotent**. The product t-norm is strict, the Lukasiewicz t-norm is nilpotent.

Formula: minimum (x, y) * terminos1 where terminus = (x+y) >1[7]

Definition of Choquet Fuzzy Integral

Let us suppose that _ be a fuzzy measure on *X* , then Choquet integral of a function f : X->[0, ∞] w.r.t fuzzy measure g is defined

$$\int f\,dg = \sum_{i=1}^{n} (f(x_i) - f(x_{i-1}))\, g(A_i)$$ where A_i is a subset of X for i = 1, 2,…n

where { $f(x_1)$, $f(x_2)$,………$f(x_n)$} are ranges and they are defined as where $f(x_1) \le f(x_2) \le \ldots \le f(x_n)$ and $f(x_0)=0$ [6]

4. Experimental Results

The following experiments were conducted to evaluate the performance of theproposed system. In the first phase all the base CNN's like VGG16, Resnet50[8], Densenet121[9] and InceptionnetV3 were used to predict the probability score of the three target classes. The accuracies of the four base CNNs are as shown in Table 1

	Time(sec)	Best_val_acc	Accuracy
VGG16	4200	0.915567	91.5567
RESNET50	3922	0.911609	91.1609
DENSENET121	3986	0.898417	89.8416
INCEPTIONNETV3	3983	0.894459	89.4459

Table 1 Accuracy and Training Time for Base Models

In the second phase various variants of fuzzy measures were used to aggregatethe predictions of the individual CNN's as expected the accuracies showed an improvement over accuracies of individual base models as shown in Table 2 Choquet Integral with t-norms are compared. The comparison shows that Nilpotent t-norm is giving the highest accuracy of 92.08%. The precision and recall play an important role in establishing the strength of the model. The precision and recall is calculated by the following formulas Precision = TP/TN+FP
Recall = TP/TN+FN

Fuzzy measures	Precision	Recall	F1-Score	Accuracy
Lukasiewicz	0.9089	0.9257	0.9136	0.9103
Hemaecher	0.9145	0.9387	0.9207	0.9182
Nilpotent	0.9208	0.9349	0.9248	0.9208

Table 3 Precision and Recall Measures of Various t-norms

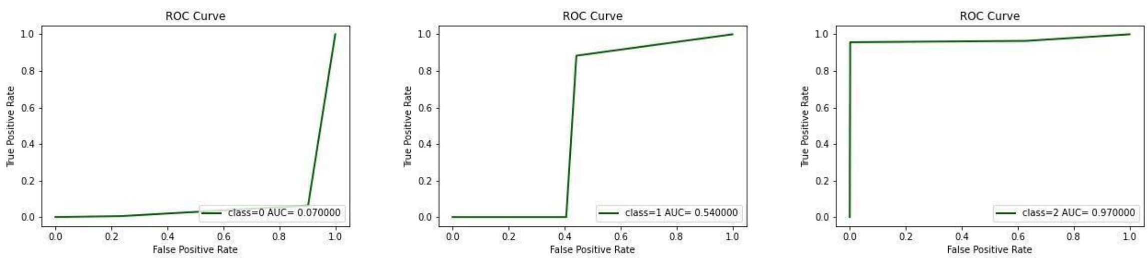
Table 3 shows the precision and recall values of all the combinations of t-norm based fuzzy measures. The model with highest value of recall will be preferred as high recall value means the percentage of false negatives is less. From this perspective Hemaecher t-norm is best.

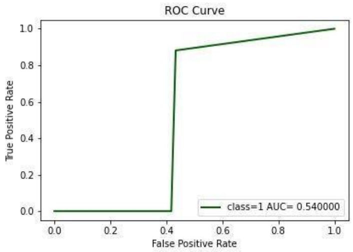
To prove this, point the various ROC curves for the target classes namely NORMAL, PNEUMONIA and COVID are drawn for all the combination of
t-Norm. Even AUC scores are also calculated for all the curves. This is shownin Figure 3

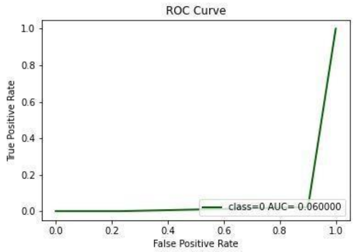
5. Conclusion and Future Scope.

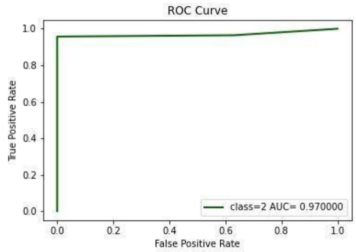
This proposed system was evaluated by using a publicly available datasetsconsisting of chest X-ray images of normal, covid and pneumonia infected patients from IEEE and Kaggle. From the experiments conducted it can be concluded that ensemble models perform better than individual models.
Moreover, it can be seen that Hemaecher t-norm is a better fuzzy measure by considering recall as the metric whereas by considering accuracy as the performance metric Nilpotent t-norm is to be preferred. The future work to be undertaken includes conducting experiments with more data as well as testing it in a practical clinical scenario.

Figure 3 ROC curves and AUC scores for various t-norms









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