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Performance of Non-Monotone Versus T-Norms Fuzzy Measures in Fuzzy Logic using Covid-19 Chest X-ray images Data

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Abstract

Covid-19 declared by WHO as a global pandemic leading to millions of deaths. In this paper Choquet integral with non-monotone fuzzy measure is compared with the variioust -norms fuzzy measures. 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, InceptionV3 and Densenet121. These pretrained CNN models were finely tuned and thenused as classifiers for the chest X-ray images. After that the prediction results of the individual models are aggregated using Choquet integral with non-monotone and t-normfuzzy measures and the final labels are predicted. Choquet Integral with t-norm fuzzy measure outperforms Choquet Integral with non-monotone fuzzy measure. In order to evaluate the proposed model , chest X- ray images from public repositories like IEEE andKaggle were used. Choquet Integral with t-norms provides 92.08% accuracy. The results of t-norms fuzzy measures are better than the results of the Choquet integral with non- monotone fuzzy measure..

Keywords: Choquet Fuzzy Integral, Non-Monotone, t-norms, fuzzy measures

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 speciality of COVID-19 is it has very long incubation period. A person may appear healthy but infact can be a asymptotic carrier of thisvirus. Inspite of the vaciination drive new variants continue to emerge which becomes a challenge to stop the propagation of this disease. So it is now the needof 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 Xray images as well as CT images. This study is solely based on analyzing Chest Xray images to detect the infected persons. Chest Xray are less expensive than CT scans. So the aim of this study is to develop a method which is inexpensive as 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 Image Net datasets which has millions of 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 CNN's 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 ensembling technique is being applied. In the area of ensembling instead of using the basic ensembling techniques like weighted average, majority voting it was decided to use fuzzy intgerals with fuzzy membership functions for aggregating the individual predictions. Another reason for applying ensembling 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 and Inception net V3 were aggregated using Choquet Integral with non-monotone fuzzy measure and were compared with the Choquet Integral t-norms-fuzzy measure.

2. Related Work

The fast spread of COVID-19 globally and its disastrous effects on the health and 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 pretained CNN's like Resnet18[8],Restnet50[8] ,Squeezenet [10] and Densenet 121[9] applied transfer learning to account for the small dataset size and proved that Squezenet[10] and Resnet50[8] gave better accuracy in prediction 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 study the author has used pretrained Alexnet for feature extraction which were passed to Relief 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 Inceptionv3.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 ensembling method stacking and weighted average to combine the results of three pretrained CNN models(VGG19,Densenet201,Resnet50) to analyse CT images for covid-19 detection. Stacking was applied at two levels 2- way stacking and three-way stacking.

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 ensembling technique is that they are not dynamic. In this case Choquet integral with non-monotone as well as t-norm fuzzy measure is used to ensemble the CNN's(VGG16,Resnet50,Densenet121 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 in any of the earlier studies.

In this paper fuzzy classifier is used as an ensemble technique.Various t-norm based 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 Figure1

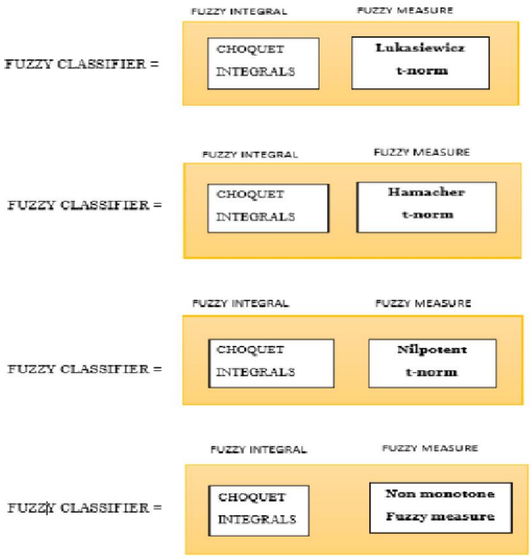

Figure 1 Different Combinations of Fuzzy Classifiers

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 shown in Figure 2

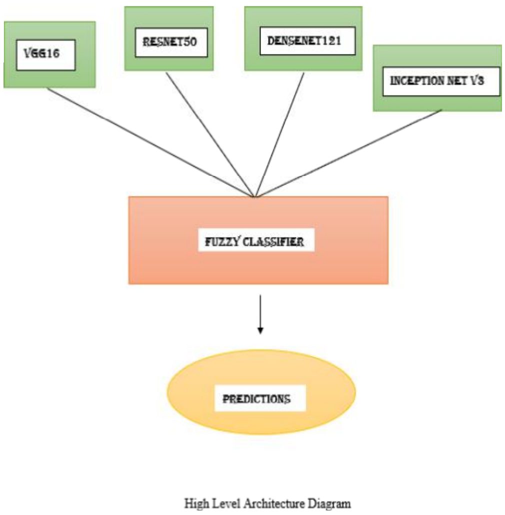

Figure 2 High Level Architecture of proposed system

Non monotone Fuzzy Measure

Consider a set X = {a, b, c}, we introduce a function μ such that μ ={0,0.9,1,0.6,0.8,0.6,0.9,1.3} .This is an example of non-monotone fuzzymeasure {a} ⊂ {a,c} -> μ(a) ≥ μ(a,c)[6]

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]

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. ContinuousArchimedean 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 afunction f : X->[0, ∞] w.r.t fuzzy measure g is defined

$\int f\,dg = \sum^{n} (f(x_i) - f(x_{i-1}))\, g(A_i)$ where A_i is a subset of X for i = 1, 2,…ni=1
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 $f(x_0)=0$

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

The experiments were conducted using 50 epochs ,SGD optimizer, learning rate of .001 and loss function as categorial crossentropy.Test set consists of around 134 covid-19 images,234 normal patient images and 390 pneumoniaimages.

In the second phase various variants of fuzzy measures were used to aggregate the predictions of the individual CNN's as expected the accuracies showed an improvement. The accuracy of Choquet integral with various t-norms as fuzzy measure is more in comparison to Choquet Integral with non-monotone fuzzy measure compared. The comparison shows that non-monotone fuzzy measure has accuracy of only 89.97% where as all t-norms exhibit an approximate increase of 2-3% .

The precision and recall play an important role in establishing the strength ofthe model. The precision and recall is calculated by the following formulas Precision = TP/TN+FP

Recall = TP/TN+FN

Comparisons of Precision and Recall measures of the various fuzzy measuresare as shown in Table2 . ROC curves as shown in figure 4

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
Non-Monotone	0.8998	0.9189	0.9058	0.8997

Table 2 Precision and Recall Measures of Various non-monotone and t-norms

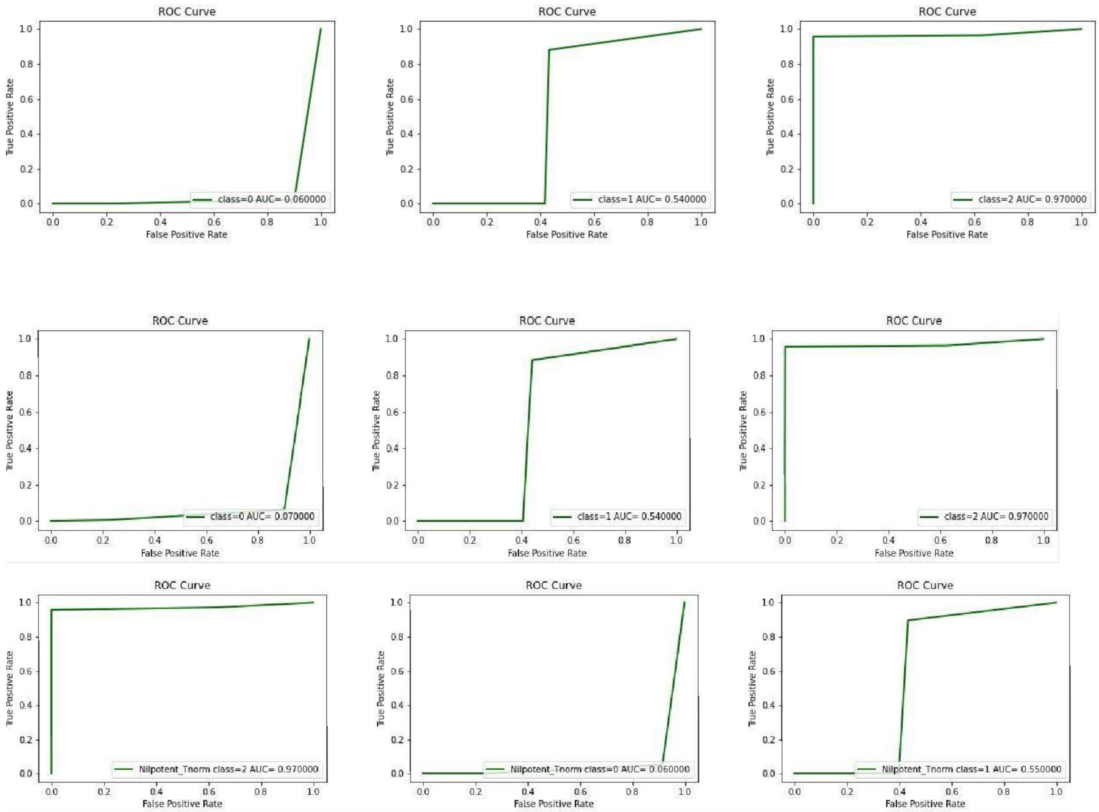

Figure 4 ROC curves and AUC scores for various t-norms

5. Conclusion and Future Scope.

This proposed system was evaluated by using a publicly available datasets consisting 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 all the various t-norms is a better fuzzy measure than non-monotone fuzzy measure considering accuracy as the performance metric.The future work to be undertaken includes conducting experiments withmore data as well as testing it in a practical clinical scenario.

6. References

[1] Shervin, Minaee, Rahele, Kafeih, Milan, Sonka, Shakib, Yazdani. Deep -COVID : Predicting COVID-19 from chest X-ray images using deep transfer learning. Medical Image Analysis Volume 65,October 2020,101794.

[2] Weiqiu Jin,a,1 Shuqin Dong,b,1 Changzi Dong,c and Xiaodan Yed,∗. Hybrid ensemble model for differential diagnosis between COVID-19 and common viral pneumonia by chestX-ray radiograph.

[3] Amit Kumar Das,Sayantani Ghosh,Samiruddin Thunder ,Rohit Dutta,Sachin Agarwal,Amlan Chakrabarti Automatic COVID-19 detection from X-ray images using ensemble learning with convolutional neural network.

[4] Mohamed Mouhafid *, Mokhtar Salah, Chi Yue and Kewen Xia Deep Ensemble Learning-Based Models for Diagnosis of COVID-19 from Chest CT images.

[5] Rohit Kundu , Hritam Basak , Pawan Kumar Singh , Ali Ahmadian , Massimiliano Ferrara & Ram Sarkar Fuzzy rank-based fusion of CNN models using Gompertz function for screening COVID-19 CT-scans.

[6] Choquet and Sugeno Integrals. Muhammad Ayub.

[7] http: / / www.scholarpedia.org / article / Triangular_norms_and_conorms

[8] He K. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2016. Deep residual learning for image recognition.

[9] Huang G., Liu Z., Maaten L.V.D., Weinberger K.Q. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2017. Densely connected convolutional networks; pp. 4700–4708.

[10] Iandola, F. N., Han, S., Moskewicz, M. W., Ashraf, K., Dally, W. J., Keutzer, K., 2016. SqueezeNet: Alexnet-level accuracy with 50 × fewer parameters and < 0.5MB model size.arXiv:1602.07360

[11] A. Garain, A. Basu, F. Giampaolo, J.D. Velasquez, R. Sarkar, Detection of covid-19 from ct scan images: a spiking neural network-based approach, Neural Comput.Appl. (2021)1–14.

[12] S. Sen, S. Saha, S. Chatterjee, S. Mirjalili, R. Sarkar, A Bi-stage feature selection approach for Covid-19 prediction using chest Ct images, Appl. Intell. (2021) 1–16. [13]F. Shan, Y. Gao, J. Wang, W. Shi, N. Shi, M. Han, Z. Xue, Y. Shi, Lung Infection Quantification of Covid-19 in Ct Images with Deep Learning, 2020 arXiv preprint arXiv:2003.04655.

[14] O. Gozes, M. Frid-Adar, H. Greenspan, P.D. Browning, H. Zhang, W. Ji, A. Bernheim, E. Siegel, Rapid Ai Development Cycle for the Coronavirus (Covid-19)Pandemic: Initial Results for Automated Detection & Patient Monitoring Using Deep Learning Ct Image Analysis, 2020 arXiv preprint arXiv:2003.05037

[15] S. Hu, Y. Gao, Z. Niu, Y. Jiang, L. Li, X. Xiao, M. Wang, E.F. Fang, W. Menpes- Smith, J. Xia, et al., Weakly supervised deep learning for covid-19 infection detection and classification from ct images, IEEE Access 8 (2020) 118869–118883.

[16] Q. Ni, Z.Y. Sun, L. Qi, W. Chen, Y. Yang, L. Wang, X. Zhang, L. Yang, Y. Fang, Z. Xing, et al., A deep learning approach to characterize 2019 coronavirus diseasteje (covid-19) pneumonia in chest ct images, Eur. Radiol. (2020) 1–11
[17] A. Banerjee, P.K. Singh, R. Sarkar, Fuzzy integral based CNN classifier fusion for 3D skeleton action recognition, IEEE Trans. Circ. Syst. Video Technol. (2020) 1–10,https://doi.org/10.1109/TCSVT.2020.3019293.
[18] Polsinelli, M.; Cinque, L.; Placidi, G. A Light CNN for Detecting COVID-19 from CT scans of the Chest. arXiv 2020,arXiv:2004.12837.