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A comparative knowledge base development for cancerous cell detection based on deep learning and fuzzy computer vision approach

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Abstract

Cancer was once thought to be a chronic fatal disease, but now it is proven to be a myth. This is due to rapid advancements in artificial intelligence (AI) techniques used to detect cancer early by collecting symptoms or analysing cancer images. Various research projects are underway to automate early cancer detection and display a perfect diagnosis plan using AI. Since early accurate diagnosis and detection of cancer disease can increase the survival rate, the present research study aims to build a model equipped with both deep learning and FCVT techniques, so that a comparative analysis between both the techniques for cancer image analysis can be done for deriving the best approximate result before the final decision is taken by the healthcare professionals. The model proposed for analysis is also tested on a standard dataset of cancer cell images and showed 95% accuracy. Hence the present study is done with a hope to design the models so that it can act as an augmentation tool to the existing healthcare facility for cancer disease forecasting and assist clinical oncology domain.

Keywords FCVT · AI · Cancer image analysis · Diagnosis

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1 Introduction

AI, machine learning, and deep learning techniques in cancer image analysis abet a lot to healthcare application. The techniques potentially improve cancer diagnosis, management and constructive therapy plan. Ontological care in the present days review over different AI oriented techniques as well as the ability of machine learning and deep learning models that are commonly associated with iterative self-learning algorithms from various sets of trained data. In cancer control, AI-based therapeutics play a vital role as a service provider to the patients. For scaling up treatment it gives precise information service in timely manner. On the same hand FCVT techniques and deep learning algorithms are considered as innovative approaches to detect cancerous image from an image file [2] .So taking into consideration the potency of both the approaches, the incremental effectiveness offered by the present research is associated with two stage process one from deep learning and another from FCVT analysis. The present research has made a comparison study between deep learning techniques and FCVT analysis that can expose training data for cancer image analysis rigorously. Consequently, the exhaustive analysis of cancer image can use a cascading combination of both deep learning algorithms and FCVT techniques as a progressive plan to use a dichotomous hierarchy that would further build up a more sophisticated model for image analysis in oncology domain [14, 19, 21].

However, this research progress is intended to mitigate existing hurdles of data management, image pre-processing, and comparative analysis of precision.

The paper is systematized as follows. Section 2 briefs the related research studies done so far for cancer diagnosis, prediction and analysis using machine learning, deep learning algorithms and fuzzy neural network. Section 3 outlines the proposed methodology of the present research with need based experimental outcomes from both FCVT techniques and deep learning algorithms for cancer image analysis. Section 4 portrays the architectural description of the deep learning model used in the current study. As the microscopic image of blood cell projects a pattern of cancerous substance whether it is present or not, hence this feature in our study is resolved by the training process of deep learning. Further the replacement of morphological analysis of blood cell is fulfilled by FCVT. Then Section 5 justifies that the detailed result analysis of haematological image by FCVT and CNN (Convolution neural network). The section also narrates the automated identification of cancer image which goes through a comparison analysis of deep learning and FCVT to achieve better accuracy. Finally Section 6 gives the concluding remarks with future scope of the work.

2 Related work

The evidential literature survey is carried out in the present research so that new validated and well justified standards can be established to identify and detect cancer disease well before time and subsequent measures can be taken. AI, machine learning as well as deep learning have been used and proved to be beneficial in various fields of healthcare. The application of AI has allowed enhanced prediction and identification of diseases like cancer, heart related diseases, nerve problems and diabetes on time.

The work in [4, 13] developed a model driven architectural tool which can be used by people with zero programming ability to develop deep learning models for cancer healthcare diagnosis and analysis. Further the work demonstrated the use of DLS tool to build deep learning models to classify the dermal cell images on standard datasets. The work also achieved an accuracy under the curve as 99.77% for the detection of cancer cells from the standard images. The study in [5, 17] developed an intelligent medical diagnostic system using neuro-fuzzy inference system for renal cancer diagnosis. The work further suggested that the method can be helpful for the doctors to identify the stage of renal cancer and thus can be used to save the life of the patients from the deadly disease at an initial stage [10]. The performance of the system is also evaluated with various parameters and achieved a classification accuracy 96%. The work in [3] experimented and analysed cancer by using various datasets containing digital and dermatological images. The research study adopted graph theory and fuzzy number-based approximation in order to get improved classification accuracy [18, 20]. The research work in [21] proposed a multi-criteria decision support system with a user-friendly interface that requires minimum sampling for predicting the cancer risk of oral malignant disorders. Further they have suggested that their proposed work can be used as a clinician's aid for monitoring the important medical decisions in future. Mainly the work has given importance to oxidative stress as it is correlated to carcinogenesis [15]. Thus the work has adopted fuzzy logic for estimating oxidative stress related cancer risk in patients. The research in [12] proposed an intelligent adaptive neuro-fuzzy system for the young doctors to help in the identification of renal cancer and its affected stage. They further said that such type of tool can act as an assistance for the doctors with less experience and can be used in the locations with less resources against the requirements. The work also evaluated the performance of the proposed system to provide accurate diagnosis of renal cancer. The research also debated on the fact that fuzzy logic deals with imprecise data and the limitation of the fuzzy logic of not being capable of adapting itself according to the environment is overcome by neural network. The research work [7, 8] debated that deep learning algorithms are best suited for medical image analysis, face recognition, and emotion recognition. Further in the survey study the work concluded that deep learning methods are proved to be beneficial for tumour detection, segmentation, feature extraction and classification. The work also narrated the three modes of deep learning approaches as training the model from the scrape, transfer learning by freezing some layers of the deep learning network and adapting the architecture to work with reduced no of parameters. The research study in [16, 25] adopted two different convolutional neural network models (MobileNet and InceptionResNet V2) for automatic identification of four parental cancer cell line (COLO 704, EFO-21, EFO-27 and UKF-NB-3) and their sublines adapted to the anti-cancer drugs cisplatin (COLO-704r CDDP1000, EFO-21r CDDP2000, EFO-27r CDDP2000) or oxaliplatin (UKF-NB-3r OXALI2000). Further the work proved that InceptionResNet V2 accomplished an average of 0.91 F1-score on tenfold cross validation with an average area under the curve (AUC) of 0.95. The study concluded that the deep learning can be employed for the automation of cell line authentication as a readily easy-to-use methodology that can enable the routine monitoring of the identity of cell lines including isogenic cell lines. The work also justified that the techniques like transfer learning and data augmentation significantly improved the model's performance. The research study in [23, 24] adopted different AI oriented techniques like fuzzy logic, Artificial Neural Networks, Particle Swarm Optimization and Fuzzy Neural for diseases like cancer, TB, diabetes, malaria, orthopedics, obesity. The work made a comparative analysis of all AI oriented healthcare analysis works and highlighted the challenges, risks and suggestions for improving the healthcare analysis with AI specifically with deep learning applications. The work also illustrated that the application of fuzzy logic got major benefits in cancer disease analysis, hence suggested the merging of AI techniques with cloud computing, IoT and deep learning to get more effective treatment, diagnosis and prediction. The research study in [14] mentioned that the identification of breast cancer as a challenging problem now a days. The authors highlighted the limitations of machine learning in breast cancer classification as it best suited for linear data. They also concluded that the machine learning algorithms fail when the data are the images. So the authors in their research suggested the use of deep learning techniques for classification of breast cancer [27]. They adopted CNN to extract best features from cancer images for its classification and proved its efficiency against machine learning algorithms. The study in [11] also employs fuzzy logic based data mining approach that can deliver a conclusive remark to image processing and early detection of breast cancer. The work carried out in [1, 29] also demonstrated the application of deep learning algorithms for breast cancer diagnosis and brain CT scan image analysis respectably. The research in [26] carried out to assess the breast cancer risk in western region of Tamil Nadu in India. The authors in their work discussed the soft computing techniques like ID3 algorithm, Association Rule and Fuzzy Expert System for predictive decision making in breast cancer disease. Further the work proposed and designed a fuzzy expert system that can be used by the doctors for diagnosing breast cancer. Moreover the work predicted the cancer intensity using Fuzzy logic toolbox. Also the mammography images are analysed with the applications of AI to classify the cancer tissues in [9]. The research study carried out in [22] showed the applications of deep learning for lungs cancer disease screening from CT scan images The machine learning as well as AI based algorithms are also applied for abnormality detection and classification of Gene expression data, which are further used for identification of cancer cells in [6, 28]. The research study in [12, 16] also made a comparative analysis between deep learning and FCVT for early detection of cancer disease. Further the accuracy and efficacy of FCVT techniques for cancer disease image analysis is described in the research work [8, 14, 26].

So it is concluded that in recent years cancer disease is considered as a fatal ill ness if it will not get attention at an early stage. Though many research works are done to analyze cancer image with the help of AI, machine learning, deep learning techniques, the need of the hour is to employ and address techniques to get timely better accuracy results in disease diagnosis. So the present research aims to carry out a comparative analysis between deep learning and FCVT techniques, so that the experimental case analysis can add on a twofold verification in achieving accuracy for cancer cell image processing and analysis wherever needed. Such conclusive research outcomes can further act as an assisting tool for the doctors, patients and medical personnel's to analyze different stages of cancer in order to reduce the mortality rate.

3 Proposed methods

Deep learning algorithms are sophisticated approaches towards disease prediction as it provides high dimensional feature diagnosis from bio medical images with greater accuracy. It progressively reviews on various types of disease detection and early monitoring from the disease dataset. Deep learning in comparison to traditional machine learning algorithm involves the usage of hierarchical neural network that mimics the behaviors of human brain and thus contributes a major technological shift in the field of machine learning. The information processing in deep learning interprets ReLU activation function which is a rectified linear unit activation function. It is best suited for contextual and visual feature extraction. Also such activation function gives better training for deeper network. Many AI based researches are going on in the field of cancer detection but improved learning accuracy is the major challenge for computer aided disease diagnosis and detection. In healthcare industry recent developments are focusing upon deep learning for many disease prediction like Dengue, Alzheimer's disease, Parkinson's disease and cancer. Deep learning allows the hyper parameter to be changed automatically when any new set of data comes from external world. So it significantly improves learning rate in model without explicit programming from human side. Gradually it explores recent advancements in risk factor analysis and assisting medical expert in effective decision making for several diseases.

On the other hand, computer vision significantly extracts, analyses, and stimulates the behaviour of an image to bring a transformational change into it. So fuzzy computer vision tool box (FCVT) provides an emerging domain in contextual understanding of an image, event detection and many complex applications. The generalized pipeline flow of computer vision algorithm can be stated as

1) Acquisition of image,
2) Pre-processing of Image,
3) Feature extraction,
4) Classification.

FCVT classifies rank of each image based on the fuzzy qualitative rank classifier (FQRC), that precisely overcomes the limitation in crisp application and ordinary fuzzy inference system (FIS). FCVT is built on existing well known technology of Python library and Open CV that can test and train dataset with an ease. The tool is also suitable for many morphological operations. An image may contain many imperfections like noise and gaps between picture elements. So FCVT tool can be used to apply certain morphological operation to filter the noises. The images to this tool box can be supplied with labels and subsequently the model can be trained with a fixed set of images. Then the classifier can be trained to classify an image. FQRC deals with training function "CL_FQRC_Train" that provides membership function to each set of image."CL_FQRC_Predict" is used to predict a new input by using FQMF generated from training step. Then the end user can visualize the result by inputting "visualize = True". Subsequently " CL_FQRC_Train "can take train images from "X-Train" and "Y-Train" and provide a label class to each image. In this manner feature dimension of each class can be generated for cancerous cell detection which in turn can provide some confidant value either for cancerous or non-cancerous data. For example if confidant value for cancerous is more than non-cancerous then image is considered as cancer cell image and based on testing one can go for quality assessment of an image with confidant label as shown in Fig. 1.

Taking into consideration the advantages of both deep learning neural network and FCVT toolbox the present research study employs image classification technique to detect the images whether it is healthy or cancerous with deep learning neural network and fuzzy computer

Fig. 1 Confidant value of each image

vision toolbox. The fuzzy code as well as functions are modified in the present work according to the need of the experiment. The experimental dataset is divided into training set and testing set to predict the model accuracy.

Eight convolution layers are used to build the convolutional neural network, starting with the input layer. The number of epochs, training and testing array are mentioned for accuracy detection in model 'model. Fit'. Then the model is generated by iterating over the number of epochs as set. In the present work 50 epochs are used. And that causes an accuracy of 95% with minimum loss. But when the number of epochs are increased, the accuracy falls drastically after a certain point due to the overfitting. Hence, the images are classified with the prediction of the results by the model whether it is healthy image or cancerous image throughout the testing dataset.

Fuzzy approach is widely used in control system with the incorporation of Fuzzy Inference system (FIS). But the nature of computer vision task is likely to deal with high dimensional feature input, it may cause some issues related to the direct application of FIS in the present study. Some of the issues can be briefed as.

i. It can be a tedious job in manual determination of the membership function for each feature.
ii. It may be impossible to produce the associate rules for high dimension feature space.
iii. It can create complexity in inference based on extensive rules.

So, in order to avoid the above said issues, FQRC is proposed with the strength that it is capable of performing feature learning to automate the fuzzy membership generation, as well as the inference not being governed by any rules. At the end of the process, FQRC is capable of generating the answer in terms of the ranking result to annotate different confidant values. Such types of interpretation is close enough to human reasoning ability for ambiguous cases.

FQRC generally consists of four stages:

1) Pre-processing (feature extraction).
2) Learning model (fuzzy membership generation).
3) Inference and.
4) Ranking interpretation.

In the Fuzzy classification, it generates the membership function for every feature dimension (number of feature dimension depends on the feature descriptor). In a theoretical concept in the learning model, it learns the image data with parametric approximation of the membership function where the membership distribution of a normal convex fuzzy number is approximated by the 4-tuple. First membership function for each feature and class is generated using histogram. Based on the number of class in the training folder, the system automatically generates the corresponding membership function that represents each feature dimension for each class.

As per the methods mentioned above in the present work the dataset is trained by invoking those functions with extraction of features from the image and then classification is done into its respective clusters. So in this way all the images present in the training folder are trained and after getting the training result the images are tested based on the Key point (in case of SIFT or SURF) and LBP detection to get the results.

4 Model architecture and the merged code

Prior to building the model all the necessary libraries are imported and path setting is specified for **'Training'** and **'Testing'** images. For the present study the Image size is taken as 28 × 28., learning rate is set as $1e^{-3}$. All the images are converted into Gray scale and also into fixed sized dimensions. The healthy images which are taken for training and building the model will return the value [1,0] and the un-healthy images will return the values [0,1]. The list containing the image data are shuffled so that no two same labelled data are side by side. Finally, the values are stored into a numpy array and fed into the network in the later steps.

The convolutional neural network is built using the Deep Learning and TensorFlow. Tflearn which is an abstraction layer for Tensorflow, is used in the model building procedure of 8 convolution layers as follows

```
convnet = input_data(shape=[None, 28, 28, 1], name='input')
```

Next, we have 8 layers of convolution and pooling:

```
convnet = conv_2d(convnet, 32, 2, activation='relu')
convnet = max_pool_2d(convnet, 2)

convnet = conv_2d(convnet, 64, 2, activation='relu')
convnet = max_pool_2d(convnet, 2)
```

Then we add a fully connected layer:

```
convnet = fully_connected(convnet, 1024, activation='relu')
convnet = dropout(convnet, 0.8)
```

Now for the output layer:

```
convnet = fully_connected(convnet, 10, activation='softmax')
convnet = regression(convnet, optimizer='adam', learning_rate=0.01,
loss='categorical_crossentropy', name='targets')
```

Now to create the model:

```
model = tflearn.CNN(convnet)
```

The model architecture is shown in Fig. 2. In this step, the test data is split into Test_x and Test_y for determination of experimental accuracy. Model.fit is used for building the model by mentioning the number of epochs, iterating over the number of epochs and by giving the train and test array. In the present study for model building 50epochs are used as because the accuracy achieved at this is 95.57% and also loss is minimum. If the number of epochs are increased, after a certain point the accuracy falls drastically, which is due to the overfitting.

5 Analysis of the merged code (i.e. Fuzzy & deep learning)

In the pre-processing for fuzzy section firstly all the required libraries are imported and then the images are pre-processed to derive the result with the test data. Python2.7 is used in the fuzzy section and python3 is used for merging the code of fuzzy and deep learning, as because in ubuntu server of aws it was possible to install the OpenCV version 3.3.0 directly using the pip3 command. In the higher or latest version of the OpenCV the SIFT and SURF is deprecated and hence feature may not be possible to use. For python3, OpenCV version 3.3.0, which is used the present study in ubuntu server of aws, the function was slightly required to be modified by cv2.xfeatures2d. SIFT create () and cv2.xfeatures2d. SURF create () to access the features. The results of the classification of the test image are stored using fuzzy in a list i.e., if it is found to be cancerous, ‘0’ is appended in the list or if it is found to be healthy, ‘1’ is appended in the list.

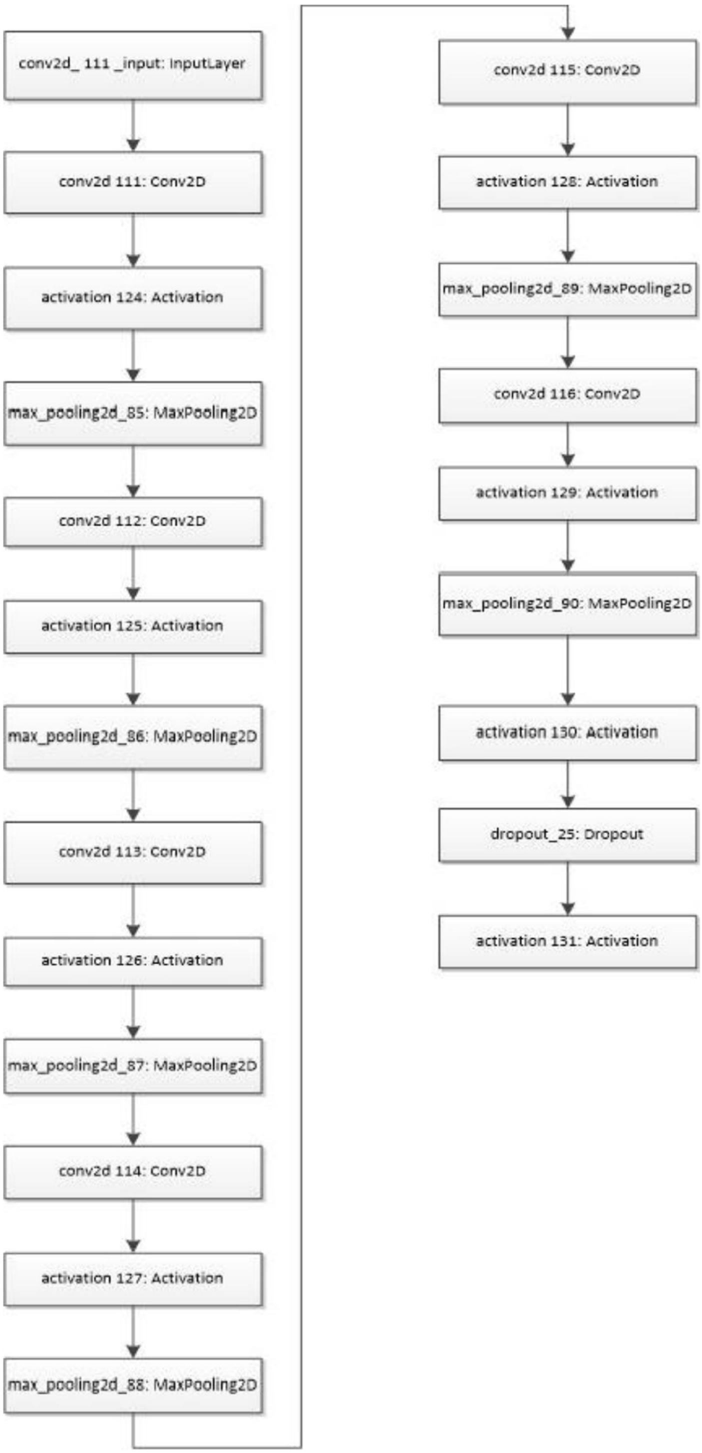

Fig. 2 CNN model architecture

```
for i in range(0,len(dirT)):
    flag=0
    if(fuzzy[i]==0 and dl[i]==0):
        flag=0
    elif(fuzzy[i]==1 and dl[i]==1):
        flag=1
    elif(fuzzy[i]==1 and dl[i]==0):
        flag=0
    elif(fuzzy[i]==0 and dl[i]==1):
        flag=1

    if flag==0:
        print(dirT[i],'--------> Cancerous Cell')
    elif flag==1:
        print(dirT[i],'--------> Healthy Cell')
```

Fig. 3 Screen shot of comparison between fuzzy and deep learning for accuracy detection

Since the classification is done using deep learning method all the libraries which are required by the deep learning classification are imported and then the said model which was created in the deep learning section having an accuracy of 95% is loaded. The recreation of the model is avoided in order to save time.

Then during the time of comparing the results whether the image is cancerous or healthy, the values present in the list of both fuzzy and deep learning are compared (as shown in Fig. 3). As deep learning gives better prediction results so the values of the deep learning are considered over fuzzy or else combinational values are taken for prediction.

- If both the fuzzy and deep learning identifies the image as cancerous then it will be predicted as cancerous.
- If both the fuzzy and deep learning identifies the image as healthy then it will be predicted as healthy.
- If the fuzzy identifies the image as healthy and deep learning identifies the image as cancerous then it will be predicted as cancerous.

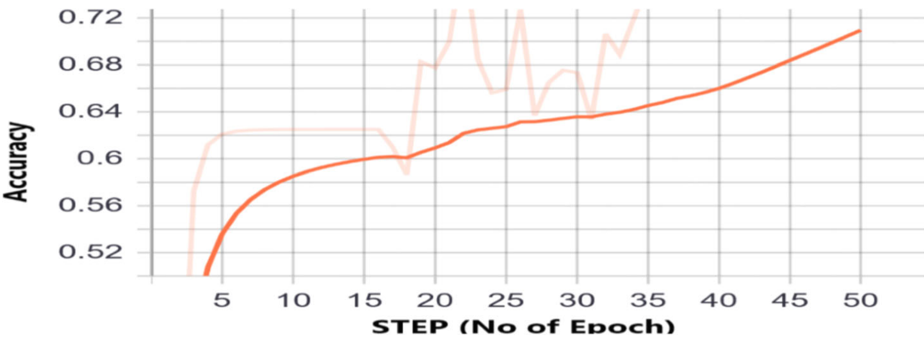

Fig. 4 Accuracy graph obtained for deep learning

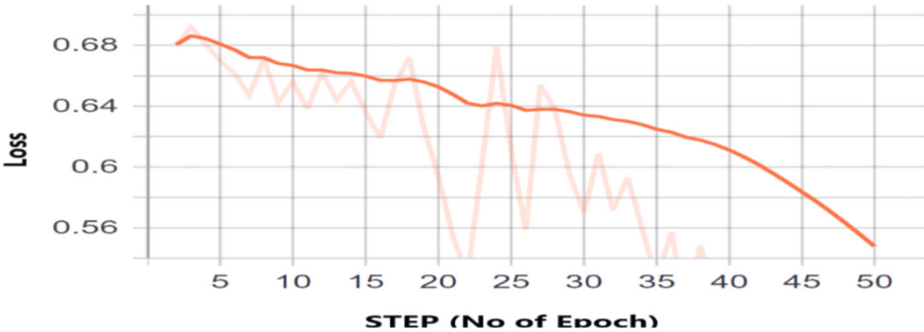

Fig. 5 Loss graph obtained for deep learning

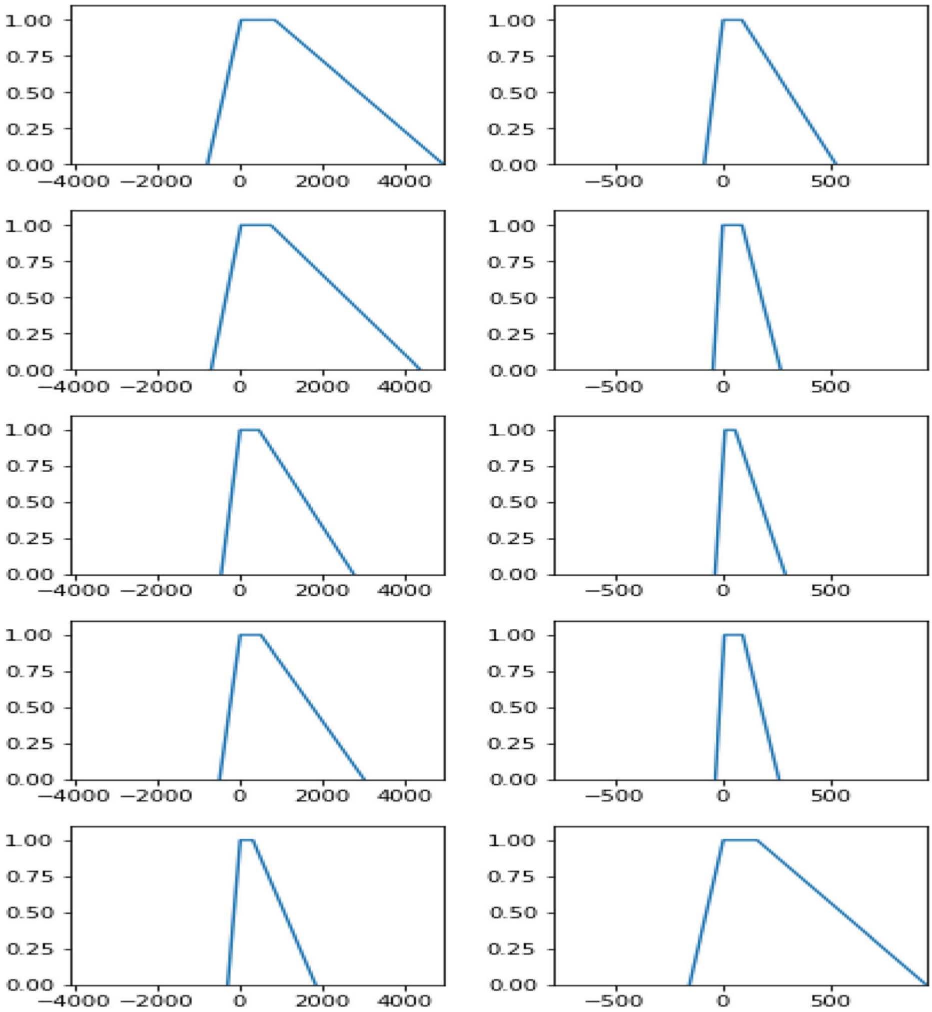

Fig. 6 Member ship obtained by FCVT tool box

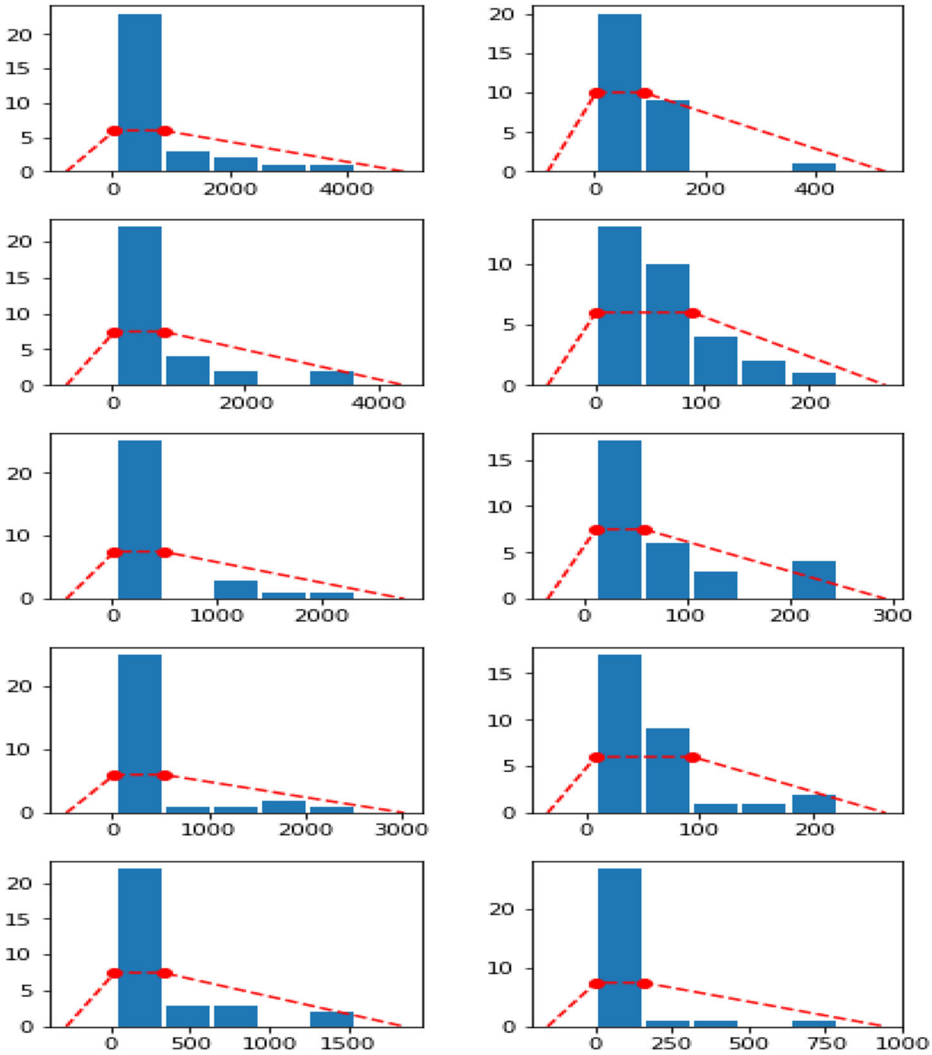

Fig. 7 Histogram obtained through FCVT tool box

- If the fuzzy identifies the image as cancerous and deep learning identifies the image as healthy then it will be predicted as healthy.

6 Results and discussion

As mentioned previously 8 convolution layers are used for building the neural network model, and the accuracy detection in the model is done through 'model. Fit' (Fig. 4).

In the deep learning the accuracy is determined by classifying the images present in the test set. This process automatically creates one-hot vector from all the categories identified in the

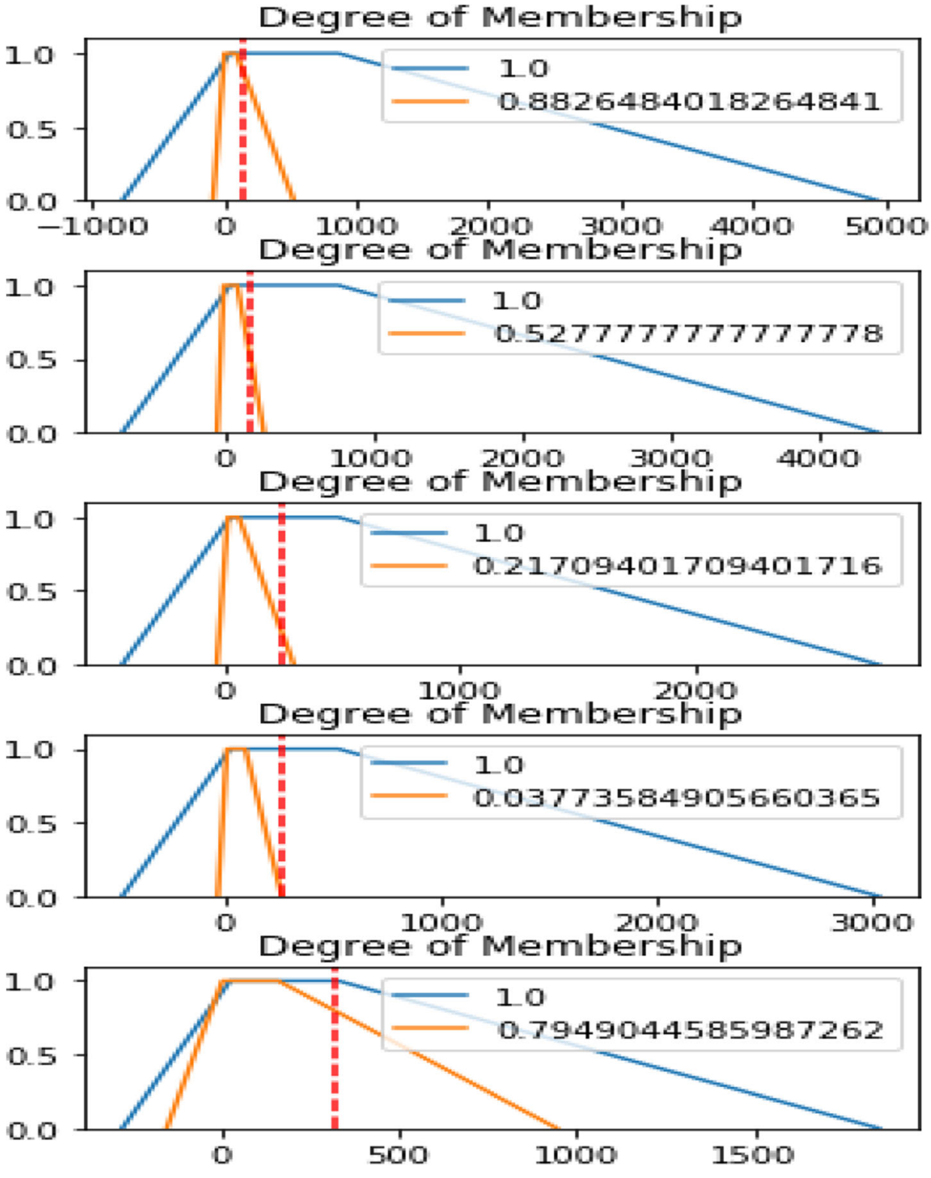

Fig. 8 Degree of member ship obtained through FCVT

dataset. Each one-hot vector can be thought of as a probability distribution, which is why by learning to predict it, the model will output a *probability* that the blood cell image belongs to any of the categories i.e. healthy or cancerous. Here numeric feature using a NumPy array is employed to specify any probability distribution as it is useful when there is a need for the model to predict an arbitrary probability distribution, or to implement label smoothing.

i. The faded line in Fig. 4 (in background) indicates the plotting with '0 smoothing' in tensorflow.

ii. The darker in Fig. 4 (orange colour) plotting represents with '0.999 smoothing' in tensorflow.

In the x-axis of the graphs there are the steps i.e. the epochs and in y-axis the value obtained from the 'model.Fit'.

The loss function which is used in this deep Learning model, is a categorical cross entropy loss function as shown Fig. 5. Categorical cross entropy is a loss function that is used in multi-class classification tasks where it can only belong to one out of many possible categories.

Formally, it is designed to quantify the difference between two probability distributions.

The FCVT analysis Output fuzzy, acc = Image_Classification('Training', 'test','SIFT', 'Fuzzy'), demands the user to provide the directory of the train folder, test folder, type of feature('SIFT'), and classification method 'Fuzzy'). Such function returns the membership values from histogram as shown in Fig. 6. The precise analysis of each image is given through histogram analysis in Fig. 7 and degree of membership of each sample image is further depicted in Fig. 8.

In the present research the deep learning model is adopted by setting model parameters, but the percentage of classification is hidden for an image. Accuracy of the model is summarized with respect to the guideline that is suitable for both deep learning as well as fuzzy classification. The model adopted in the present study has taken the advantage of of ReLU activation function and 3 × 3 filter size .A drop out percentage is 0.25 to 0.45 is taken to speed up training that resulted into 95% accuracy in 50 epochs. The max pooling layer provides spatial dimension for each image. Though many research works acquire the beauty of neuro fuzzy inference system, the present study has developed a diagnostic system by validating each image through FCVT analysis. Such analysis justifies the confident analysis of each image with an indication of similar precision by making a comparison between training set and testing data. Hence this research analysis concludes that two fold approach is more suitable for preparing a comparative knowledge base for cancer cell detection at the early stage so that it would be beneficial for both the healthcare as well as patient community. The probabilistic performance of this knowledge base development can provide precise confidant value of each image for correct prediction of cancer cell where there is scarcity of expert and adequate resource.

7 Conclusions

The early diagnosis of cancer is essential for every patient as it proposes quick treatment plan for oncological issue. Manual identification from microscope needs a lot of time, so under expert supervision a deep learning based image detection tool can enhance the blood cancer image diagnosis. The study carried out in the present paper adopted a comparative analysis between FCVT and deep learning and the experimental analysis delivered a precise identification of image by comparing the accuracy result of FCVT and deep learning model. Further the comparative result significantly compared image feature by FCVT and deep learning model to achieve acceptable accuracy at the testing phase. More over the present study concentrates upon two-fold verification first through deep learning and second by FCVT. The future extension of the present study aims to develop a fully automatic system with a combined approach of deep learning and FCVT analysis that can run in back ground on cloud in order to act as an augmentation tool for existing healthcare facilities.

Author contribution Subhasish Mohapatra and Suneeta Satpathy contributed to the conceptualization, design and implementation of the research, Sachi Nandan Mohanty and Subhasish Mohapatra contributed to the analysis of the results. All the authors have equally contributed to the writing of the manuscript.

Data availability Dataset used for analysis can be given if required.

Code availability Code can be given if required.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

1. Alshennawy AA, Aly AA (2009) Edge detection in digital images using fuzzy logic technique. World Acad Sci Eng Technol 51:178–186
2. Ardila D, Kiraly AP, Bharadwaj S et al (2019) End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography. Nat Med 25(6):954–961
3. Banerjee S, Singh SK, Chakraborty A, Das A, Bag R (2020) Melanoma diagnosis using deep learning and fuzzy logic. Diagnostics (Basel Switzerland) 10(8):577. https://doi.org/10.3390/diagnostics10080577
4. Bejnordi BE, Veta M, Van Diest PJ, Van Ginneken B, Karssemeijer N, Litjens G, Van Der Laak JA, Hermsen M, Manson QF, Balkenhol M et al (2017) Diagnosticassessment of deep learning algorithms for detection of lymph node metastasesin women with breast cancer. JAMA 318:2199–2210
5. Borglund M, Åkesson A, Åkesson B (1988) Distribution of selenium and glutathione peroxidase in plasma compared in healthy subjects and rheumatoid arthritis patients. Scand J Clin Lab 48(1):27-32
6. Chen YH (1995) Computer vision for general purpose visual inspection: a fuzzy logic approach. Opt Lasers Eng 22(3):181–192
7. Chilamkurthy S, Ghosh R, Tanamala S, Biviji M, Campeau NG, Venugopal VK,Mahajan V, Rao P, Warier P (2018) Deep learning algorithms for detectionof critical findings in head ct scans: a retrospective study. Lancet 392:2388–2396
8. Debelee TG, Kebede SR, Schwenker F, Shewarega ZM (2020) Deep learning in selected cancers' image analysis—A survey. J Imaging 6(11):121. MDPI AG. Retrieved from https://doi.org/10.3390/jimaging6110121
9. Farooq MS, Bilal HM, Ali MN, Hassan A (2018) Automation of blood cancer risk analysis using fuzzy logic. LGURJCSIT 2(2):57–63
10. Genovese G, Kähler AK, Handsaker RE, Lindberg J, Rose SA, Bakhoum SF, McCarroll SA (2014) Clonal hematopoiesis and blood-cancer risk inferred from blood DNA sequence. N Engl J Med 371(26):2477–2487
11. Jaleel JA, Salim S, Aswin RB (2013) Diagnosis and detection of skin cancer using artificial intelligence. Int J Eng Innov Technol 3:311–315
12. Jindal N, Singla J, Kaur B, Sadawarti H, Prashar D, Jha S, Joshi GP et al (2020) Fuzzy logic systems for diagnosis of renal cancer. Appl Sci 10(10):3464. MDPI AG. Retrieved from https://doi.org/10.3390/app10103464
13. Kadampur MA, Riyaee SA (2020) Skin cancer detection: Applying a deep learning based model driven architecture in the cloud for classifying dermal cell images. Inform Med Unlocked 18:100282. https://doi.org/10.1016/j.imu.2019.100282
14. Kumar SP (2021) A review paper on breast cancer detection using deep learning. IOP Conf Ser: Mater Sci Eng 1022 012071
15. Mohapatra S, Patra D, Satpathi S (2010) Image analysis of blood microscopic images for acute leukemia detection. In: 2010 International Conference on Industrial Electronics, Control and Robotics. IEEE, pp 215–219
16. Mzurikwao D, Khan MU, Samuel OW, Cinatl J Jr, Wass M, Michaelis M, Marcelli G, Ang CS (2020) Towards image-based cancer cell lines authentication using deep neural networks. Sci Rep 10(1):19857. https://doi.org/10.1038/s41598-020-76670-6
17. Nikita BK, Sadawarti H, Singla J (2020) A d intelligent system for diagnosis of renal cancer. Int J Sci Technol Res 9(01)

18. Pham TD, Wårdell K, Eklund A, Salerud G, Bilal MS, Ali HM, Hassan A (2019) Classification of short time series in early Parkinson s disease with deep learning of fuzzy recurrence plots. IEEE/CAA J Autom Sin 6(6):1306–1317
19. Putzu L, Di Ruberto C (2013) White blood cells identification and classification from leukemic blood image. In International Work-Conference on Bioinformatics and Biomedical Engineering. Copicentro Editorial, pp 99–106
20. Ramesh Dhanaseelan F, Jeyasutha M (2021) A novel fuzzy frequent itemsets mining approach for the detection of breast cancer. Int J Inf Retr Res (IJIRR, IGI Global) 11(1):36–53
21. Scrobotă I, Băciuţ G, Filip AG, Todor B, Blaga F, Băciuţ MF (2017) Application of fuzzy logic in oral cancer risk assessment. Iran J Public Health 46(5):612–619
22. Shemona JS, Chellappan AK (2020) Segmentation techniques for early cancer detection in red blood cells with deep learning-based classifier—a comparative approach. IET Image Process 14(9):1726–1732
23. Srivastava S, Pant M, Agarwal R (2020) Role of AI techniques and deep learning in analyzing the critical health conditions. Int J Syst Assur Eng Manag 11:350–365. https://doi.org/10.1007/s13198-019-00863-0
24. Tahani H, Keller JM (1990) Information fusion in computer vision using the fuzzy integral. IEEE Trans Syst Man Cybern 20(3):733–741
25. Van Ooijen H, Hornsveld M, Dam-de Veen C, Velter R, Dou M, Verhaegh W et al (2018) Assessment of functional phosphatidylinositol 3-kinase pathway activity in cancer tissue using forkhead box-O target gene expression in a knowledge-based computational model. Am J Pathol 188(9):1956–1972 [FREE Full text] [Medline: 30030980]. https://doi.org/10.1016/j.ajpath.2018.05.020
26. Valarmathi S, Sulthana A, Rathan R, Latha KC, Balasubramanian S, Sridhar R (2012) Prediction of risk in breast cancer using fuzzy logic toolbox in MTLAb environment. Int J Curr Res 4(09):072–079
27. Venet D, Dumont JE, Detours V (2011) Mostrandom gene expression signatures are significantly associated with breastcancer outcome. PLoS Comput Biol 7(10):e1002240 [FREE Full text] [Medline: 22028643]. https://doi.org/10.1371/journal.pcbi.1002240
28. Yager RR, Zadeh LA (eds) (2012) An introduction to fuzzy logic applications in intelligent systems (vol 165). Springer Science & Business Media, Berlin
29. Zareiforoush H, Minaei S, Alizadeh MR, Banakar A, Samani BH (2016) Design, development and performance evaluation of an automatic control system for rice whitening machine based on computer vision and fuzzy logic. Comput Electron Agric 124:14–22