Computer Assisted Methods in Engineering and Science
30(2): 151–165, 2023, doi: 10.24423/cames.463

This article belongs to the *Special Issue on Scientific Computing and Learning Analytics for Smart Healthcare Systems* edited by Dr. C. Chakraborty, Dr. S. Barbosa and Dr. L. Garg

Hybrid Deep Learning Method for Detection of Liver Cancer

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Liver disease refers to any liver irregularity causing its damage. There are several kinds of liver ailments. Benign growths are rarely life threatening and can be removed by specialists. Liver malignant tumor is leading causes of cancer death. Identifying malignant growth tissue is a troublesome and tedious task. There is significantly less information and statistical analysis presented related to cholangiocarcinoma and hepatoblastoma. This research focuses on the image analysis of these two types of cancer. The framework's performance is evaluated using 2871 images, and a dual hybrid model is used to accomplish superb exactness. The aftereffects of both neural networks are sent into the result prioritizer that decides the most ideal choice for image arrangement. The relevance of elements appears to address the appropriate imaging rules for each class, and feature maps matching the original picture voxel features. The significance of features represents the most important imaging criteria for each class. This deep learning system demonstrates the concept of illuminating elements of a pre-trained deep neural network's decision-making process by an examination of inner layers and the description of attributes that contribute to predictions.

Keywords: liver cancer detection, deep learning, fully convolutional neural network, hybrid approach, discrete wavelet transform (DWT).

1. Introduction

Computerized image handling uses processing to deal with advanced images by using an advanced PC. Many issues emerge in the current framework, for example, giving countless faulty rates, over-segmenting tumor regions, high time complexity, low exactness, and it is a troublesome to deal with constructions of high inconsistency with a lot of disturbances that happen during division.

1.1. Background

The dynamic shape method and deep learning calculations involve recognizing inappropriate sources of info and furnish definite results with an identical viable allowance, such as recognizing a wide range of liver problems in solitary handling. The topology of medical imaging methodologies is presented in Fig. 1.

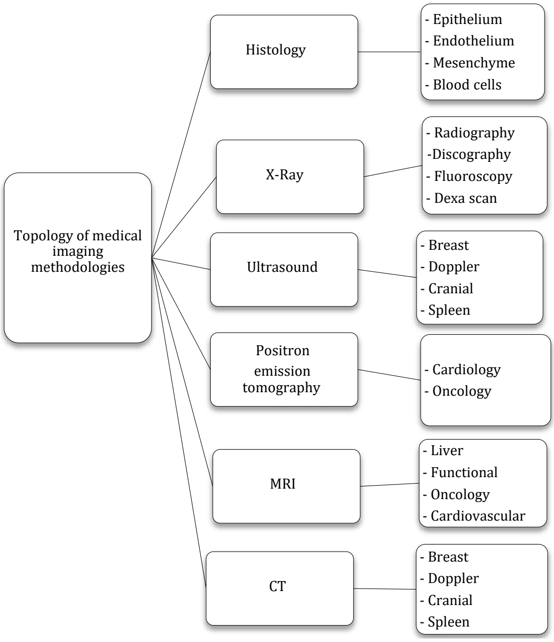

Fig. 1. Topology of medical imaging methodologies.

Hepatic carcinoma (HCC) is the subsequent reason for malignant growth deaths around the world, and it is the most normal essential cause of hepatocellular disease in individuals. Unlike other diseases, the incidence of HCC is rising [2]. Convolutional neural networks (CNNs) are useful in detecting and analyzing quickly and dependably the HCC in individuals, bringing about better results [3]. As the quality and accessibility of images have expanded, the requirement for intrusive demonstrative biopsies has diminished, driving imaging to a more fundamental position with an evident status, especially in essential liver malignancies [4]. The liver is likely the most often examined organ, and metastases are processes that aid in the detection, diagnosis, and management of hepatic disorders. The most well-known are liver diseases [5]. Prior to the injection of a contrast agent, pictures are acquired, with the entrance stage image providing the best lesion identification [6]. Such approaches demand data on lesion size, shape, and precision [7]. Manual diagnosis and segmentation are complex tasks that must be completed by the radiologist using three-dimensional computed tomography images that may contain several lesions [8]. Furthermore, the urgency of the issue emphasizes the necessity for computational assessment to aid clinicians in detecting and analyzing hepatic metastases in CT scans [9]. Because of the various contrast actions identification and segmentation has proven to be extremely challenging [10].

Deep learning is occasionally a basic way for bringing each pixel in an image up to a comparable level. For pre-processed photos, the extracted images might thus represent the features of the images themselves, and the nature of the retrieved features dictates the exactness of the task [10–12]. Finally, it was deduced that the crucial component of profound learning is visual feature categorization, which is the focus of most current research [13]. AI calculations have increased radiological proficiency and have the potential to overcome any challenges in the radiological classification of various infections [14, 15]. To recognize images, fully convolutional neural networks (FCNNs) do not require recognizable confirmation of explicit radiological qualities, and, unlike other AI methods, they may even disclose features that do not exist in radiological practice [16]. Gunasundari *et al.* [14–18] improved feature selection of excellent features from liver malignant development information using velocity bounded Boolean particle swarm optimization (PSO). When implemented in a hepatic CAD framework, the proposed technique selects the best characteristics utilised to classify hepatoma and cholangiocarcinoma as life threatening and hemangioma and focal nodular hyperplasia (FNH) as innocuous.

1.2. Motivation

The liver includes an assortment of cell types. These numerous cells join to produce different kinds of diseases. A portion of the growths are harmful and are considered life-threatening, while others are non-destructive and are considered harmless. Malignant growths in the liver are grouped into two types: primary is those that start in the liver and go to different parts of the body, while auxiliary is those that start somewhere else in the body and travel to the liver. HCC is one of the most widely recognized types of liver diseases. As indicated in [6], around 80% of liver malignant tumors among adults are of this type. Risk factors include weight, cirrhosis, sexual orientation, age, liquor consumption, and hepatitis B and C [7]. The hepatitis B infection (HBV) can cause chronic disease, cirrhosis, and liver malignant tumor, as per the World Health Organization. Previous reviews demonstrate that imaging methods, for example, ultrasound examines, MRI sweeps, and CT filters are used to recognize this type of liver disease. AI-based computer-aided detection (CADe) and computer-aided diagnosis (CADx) frameworks have become fundamental in the clinical field. Prior examinations introduced an assortment of frameworks using particular methods.

Each has advantages and disadvantages. The fundamental cycle and stages, be that as it may, are compared by everyone. Therefore, this paper depicts various procedures and calculations used in past examinations.

1.3. Classification approach

In practice, the segmentation is used access to anticipate diseases and predict clinical findings. Dong *et al.* [9] presented the hybridized fully convolutional neural network (HFCNN) approach for recognizing and segmenting liver lesions. Two key factors in such an arrangement are as follows:

1) Accuracy: it should be just about as exact as expected.
2) Computation time: this should be about as short as possible.

In light of the necessities, the conveyed features are characterized into two, three, or more classes, and characteristics recovered or chosen before steps are used in this cycle. Order is principally dependent on preparing and testing. As outlined beneath, the item can be ordered in two ways:

1) Directed: predefined classes with marked information.
2) Unsupervised: unlabeled information with obscure groupings.

1.4. Objectives of the paper

In order to obtain good results it is very important to have a proper analysis of the image. So, the present research has the following five objectives:

1) To review the various techniques for diagnosing liver cancer.
2) To process the images using the best segmentation method available.
3) Using a hybrid algorithm, extract features and categories of the processed images.
4) To identify the many forms of liver cancer (HCC, metastasis, cirrhiosis).
5) To put the performance parameters to the test and compute them.

2. Literature survey

The characterization of particular kinds of liver malignant tumors using machine help has opened up another exploration road for early disease identification. Many researchers have studied techniques for distinguishing liver diseases. A framework dependent on fractal math and a changed probabilistic neural network was made to characterize CT liver images. In light of CT images, a PC-supported methodology was used for classifying liver lesions. The classification methods are graphically shown in Fig. 2. The methods are usually classified as spatial and spectral domains.

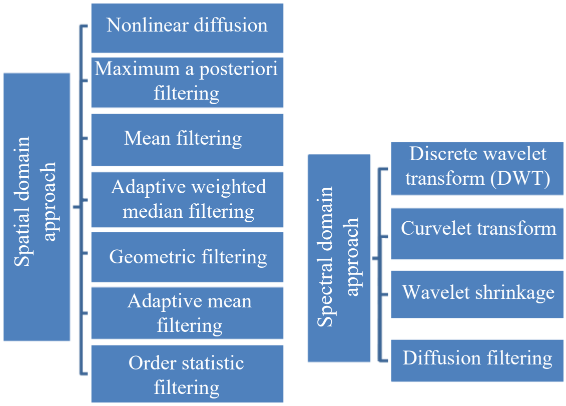

FIG. 2. Methods of classification.

Alahmer *et al.* [1] presented a CAD framework that partitions a divided lesion into three areas: inside, outside, and border segments. The information extricated from these areas was used to extract a new vector of features to feed a classifier to help with the separation of harmless and threatening growths.

Chang *et al.* [6] presented a PC-supported analytic (CAD) framework for recognizing liver malignant growth dependent on cancer qualities separated from multiphase CT images. Three classes of qualities were extricated for every growth: texture, shape, and kinetic curve. Cancer's surface was evaluated using three-layered (three-dimensional) surface information dependent on the grey level co-occurrence method (GLCM).

Gunasundari *et al.* [17] evaluated the multiswarm heterogeneous binary particle swarm optimization (MHBPSO) approach in the feature selection phase of intelligent liver and kidney disease diagnostic systems to select elite features from the liver malignant growth information. The MHBPSO calculation is a co-operation algorithm.

Gunasundari *et al.* [16] proposed ABPSO (adjusted BPSO) to further develop feature selection execution and BPSO associated speed. The technique was used in the element choice module of the liver CAD framework.

Huang *et al.* [19] showed that a convolutional neural network (CNN) might be utilized for assigning LI-RADS categories (LR-1–5) for the classification of hepatic observations on multiphase CT and MRI from a small dataset.

Kondo *et al.* [20] proposed a hybrid group technique of data handling-type neural network algorithm using artificial intelligence for the image diagnosis (ID) of liver malignant growth using clinical imaging. Textural highlights were utilized, dimensionality is decreased using a sequential forward floating selection (SFFS), and a classifier was picked.

Kumar *et al.* [21] presented a computerized framework for recognizing five levels of liver fibrosis, with the hill climbing calculation used to pick the best describes. The cooperative coevolutionary method was utilized to create a set of rules dependent on prepared tests, which were then used to portray various levels of fibrosis for the experiment.

Kumar *et al.* [22] contourlet-based features were found to surpass the gray level textural features. Kumar *et al.* [23] proposed a hepatic CAD framework for characterizing HCC and hemangiomas. Principal component analysis (PCA) is a procedure for diminishing wavelet and contourlet coefficients. The diminished elements are input into a probabilistic neural network (PNN) to separate benign from malignant growths, and the accuracy acquired utilizing the CCCM feature is 96.7%, which is higher than other features.

Kuo [24] proposed utilizing examination of CT images to enhance a PC-supported classification system for liver tumors. Lee *et al.* [25, 26] proposed two-stage choice procedure which combines an improved PSO calculation with SVM. Li *et al.* [28] presented a liver malignant growth diagnosing framework based on a BP neural network after dimensionality reduction by PCA, combining multiple features and multi-phase information. Al-Shabi *et al.* [2] concentrated on the presentation of SVM, MLP, and GRNN performances in arranging the liver tissues dataset (impacted or unaffected). Das *et al.* [8] presented a new system called watershed Gaussian-based deep learning (WGDL) procedure for effectively delineating the cancer lesions in the liver CT images.

Li *et al.* [29] recognized the liver cancer utilizing fully convolutional networks with a weighted loss function. The FCN segmentation result was then combined with the first CT image to deliver a four-channel image data that is used as an input to a nine-layer CNN classifier.

Ladkat *et al.* [31] presented the matched filter approach for preprocessing. It was used to remove unwanted parts of the medical image such, as blood vessels. So, removal of blood vessels leads to the improved accuracy in classification. Li *et al.* [29] proposed a completely mechanized CAD framework for portioning the liver and injuries just as identifying liver illness. Mala and Sadasivam [30] proposed the liver segmentation approach utilizing a mix of fluffy grouping and dark wolf streamlining, while the injury division technique utilized a quick fluffy c-implied philosophy. Example shape and surface elements are separated and utilized in a characterization stage with a help vector machine classifier [32, 33].

From the literature review it is clear that there is a need to design an algorithm based on deep neural network with additional extracted features.

3. Proposed system architecture

3.1. Flow of the system

A database of 2871 images is collected, and then for feature extraction purpose, a wavelet transform is used (flow of the classifier is shown in Fig. 3). Then,

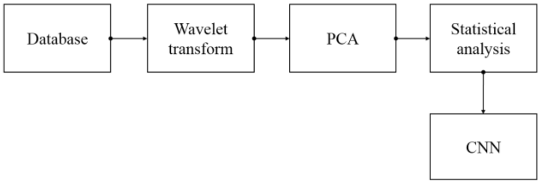

FIG. 3. Flow of the system.

to reduce the dimensionality of the features, PCA is used. The after statistical parameters are being extracted to obtain a result from the classifier.

3.2. Proposed architecture model

A dual hybrid model is used to achieve great precision. The aftereffects of both neural networks are then conveyed to the result prioritizer who settles on an official choice of image description. In the event that the aftereffects of both neural networks are comparable (which is, for the most part, the case), then, at that point, the same outcome turns into the end product. The diagrammatic representation of the proposed system architecture (PSA) is presented in Fig. 4.

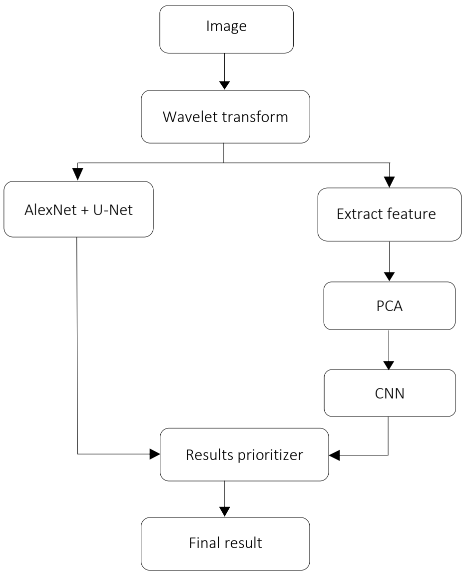

FIG. 4. Proposed architecture model.

AlexNet + U-Net: The image is initially subjected to a wavelet transform before being input into a hybrid (AlexNet and U-Net) neural network model. As a result, we get a classification result.

CNN: The wavelet transformation is also used to recover the image's properties. The PCA method is used to shorten the range of certain characteristics. The information is then fed into the CNN, which generates a result.

Assuming that the results of both neural networks are different, the choice is not determined based on priority. Cholangiocarcinoma, for instance, is given the best need, while hepatoblastoma is given the most minimal. Thus, assuming any of the neural networks conveys a cholangiocarcinoma result, cholangiocarcinoma will be a definitive end result.

3.3. Algorithm details

3.3.1. Discrete wavelet transform. The wavelet change disintegrates a sign into a bunch of crucial capacities. These essential capacities are referred to as wavelets. A discrete wavelet change (DWT) is a technique for changing a discrete real transform to a discrete wavelet transform. This can be conducted using a scaling capacity that depicts the wavelet's scaling features. The condition that the scaling capacities be symmetrical to their discrete interpretations forces extra numerical requirements on them, which are tended to all through the paper, for instance, in the enlargement condition. DWT is mainly used to decompose an image and get the maximum number of features out of it. $\phi(x)$ is the scaling function:

$$\phi(x) = \sum_{k=-\infty}^{\infty} a_k \phi(Sx - k), \tag{1}$$

where S is a scaling factor (typically picked as 2), and a_k is a sampling parameter. Moreover, the region between the capacity and the scaling capacity should be standardized, and the scaling capacity should be symmetrical to its whole number of deciphers, e.g.:

$$\int_{-\infty}^{\infty} \phi(x)\phi(x + l)\,\mathrm{d}x = \delta_{0,l}, \tag{2}$$

where $\delta_{0,l}$ is the symmetry about the number of deciphers.

We can get consequences of this large number of conditions subsequent to embedding some additional limitations (since the limitations above do not yield a significant arrangement), for instance, a limited arrangement of coefficients a, k that decides the scaling capacity and, furthermore, the wavelet. The wavelet is obtained from the scaling capacity as follows:

$$\psi(x) = \sum_{k=-\infty}^{\infty} (-1)^k a_{N-1-k} \psi(2x - k), \tag{3}$$

where N is an even whole number, and ψ is the wavelet function obtained.

The arrangement of wave lets then structures an orthonormal premise that we use to break down signals. Typically, not many of the coefficient's a, k are non-zero, which improves the computations.

3.3.2. Principal component analysis (PCA). The basic standard behind head component analysis (PCA) is to limit the dimensionality of an informational collection comprising of various factors. This is done by changing over the factors into another arrangement of factors known as the important parts (or essentially, the PCs), which are symmetrical and organized so that the maintenance of variety contained in the first factors lessens as we travel down in the request. Figure 5 shows the orthogonal trajectories of the PCA for the 1st and 2nd dimensions.

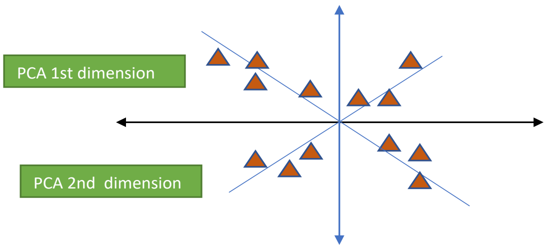

Fig. 5. Principal component analyses (PCA).

3.3.3. Convolutional neural network. CNN is a fake neural network with numerous architectures, as displayed in Fig. 6; CNN input information can be images or boundary datasets. Numerous convolutional or pooling layers follow the info layer (with or without enactment capacities). To handle grouping issues, at least one full association (FC) layer is normally used. The last layer produces forecast esteems (such as back likelihood or probability) for K different kinds of items that ought to be classified from the information image.

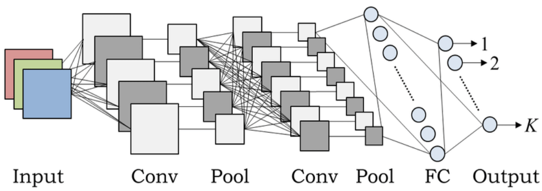

Fig. 6. CNN architecture.

Before moving toward the deep learning approach, many machine learning techniques have been tried. The result of the machine learning was very poor, so the additional feature extraction with maximum deep level learning approach is selected. Therefore, the deep level study of the extracted features has been carried out in the research.

4. Result and discussion

There are several types of liver cancer. Our study focuses mostly on cholangiocarcinoma and hepatoblastoma cancers. The system's performance is evaluated using 2871 images.

To accomplish high exactness, a dual hybrid model is used. The result of both neural networks is sent into the result prioritizer, which makes a definitive judgment on image order. Assuming the results of both neural networks are similar (which is normally the situation), then that indistinguishable outcome turns into the end product.

In the AlexNet and U-Net approach, the image is initially placed into the wavelet transform, and the created image is then taken care of in the crossbreed (AlexNet and U-Net) neural network model. Thus, we get an order result. The equivalent is performed to the wavelet transform in the CNN approach, and afterward, the images elements are recuperated. PCA is used to reduce dimensionality of the feature characteristics. The information is then processed in the CNN to get an outcome. Cholangiocarcinoma, for instance, is given the best need, while hepatoblastoma is given the most reduced one. Altogether, assuming any of the neural networks gives a cholangiocarcinoma result, cholangiocarcinoma is the last end, without paying much attention to which neural network made that outcome. This arrangement eliminates the issue of incorrect categorization. Next there are the categorization classes: 1) cholangiocarcinoma, 2) hepatoblastoma, and 3) normal.

In Fig. 7 it is clear that the eigenvalues of the confusion matrix are dominant. The accuracy of the PSA is 98.92%, which is much higher than the existing systems. The performance parameters of the proposed system architecture are

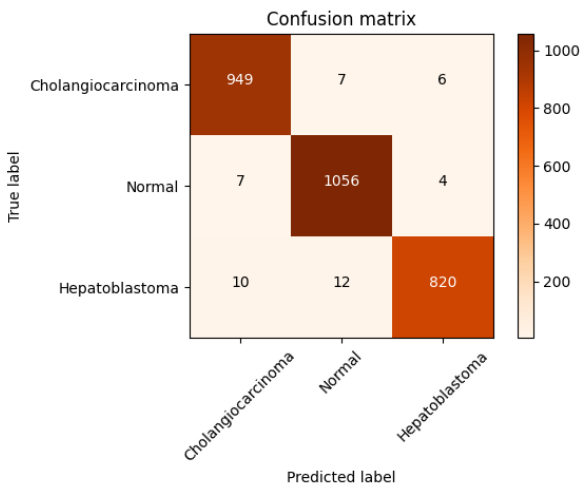

Fig. 7. Confusion matrix.

shown in Table 1. It clearly shows that all the parameters are dominant as every parameter is very close to its ideal value.

Table 1. Performance parameters from the confusion matrix.

Performance parameters	Cholangiocarcinoma	Hepatoblastoma	Normal	Over all system
Specificity	99.1	99.5	98.94	99.18
Precision	98.24	98.79	98.23	98.42
Negative predictive value	99.31	98.92	99.38	99.20333333
False positive rate	0.89	0.49	1.05	0.81
False negative rate	1.35	2.61	1.03	1.663333333
False discovery rate	1.75	1.2	1.76	1.57
Accuracy	98.95	98.88	98.95	98.92666667

The time it takes to get a result is calculated on the different processors. The average time required to get the result of different hardware platforms is tabulated in Table 2.

Table 2. The time it takes to get the result by using the proposed system architecture on different hardware platforms.

Platform	Time required to get result [s]
CPU, i3 processor, 8GB RAM	0.293
CPU, i5 processor, 8GB RAM	0.193
CPU, I7 processor, 8GB RAM	0.191
GPU, Nvidia K80	0.0026

The time required to get result on CPU with i5 and i7 processor is approximately the same. The drastic variation in time is observed in the use of GPU.

5. Conclusion

This article presented a convolutional neural network (CNN) strategy for perceiving and fragmenting liver disease and lesions. To work on the precision of clinical image segmentation, a few layers of the neural network are utilized to extricate the properties of clinical images. DWT is an apparatus for image pre-handling. A few measures, such as mean, middle, standard deviation, skewness, and kurtosis, are removed from pre-handled images using the PCA approach. CNN is utilized to study and evaluate the obtained measurable elements. There are a few types of liver malignant growths. The malignant growths of cholangiocarcinoma and hepatoblastoma are considered in this study. The framework's performance is evaluated utilizing 2871 images. A dual hybrid model is used to accomplish incredible precision. The results of both neural networks are sent to the result prioritizer, which settles on an ultimate conclusion on image order. Assuming that the aftereffects of both neural networks are comparative (which is by and large the case), then, at that point, the same outcome turns into the end product. In the AlexNet and U-Net approach, the image is initially placed into the wavelet transform, and the produced image is then taken care of in the half-and-half (AlexNet and U-Net) neural network model. Thus, we get an order result. Also, the wavelet change is utilized in CNN's method to retrieves image qualities. PCA is utilized to shorten the range of those characteristics. The information is processed in the CNN, which creates an outcome. In the event that the results of both neural networks differ, the choice is not determined based on priority. Future work can focus on the segmentation of cancer tissues in 3D medical images.

Acknowledgements

The authors would like to thank all teaching and non-teaching staff members of the Electronics & Telecommunications Department in GHRU, Amravati, and NBNSSOE Aambegaon BK, Pune, for their support. The authors also acknowledge the guidance and support of the Staff members of the Medicine Department in Smt. Kashibai Navale Medical College & General Hospital. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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Received January 10, 2022; revised version February 27, 2022; accepted April 10, 2022.