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# Multilayer Weighted Logistic Regressive Deep Convolution Neural Learning Based Feature Extraction For Liver Tumor Detection.

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**Abstract**
The diagnosing liver disease is crucial for saving lives and managing the condition effectively. The conventional techniques were implemented for liver tumor diagnosis does not provided higher feature extraction accuracy to identify the presence of cancer at an early stage with minimal time complexity while considering a more number of input images. Therefore, a new Multilayer Weighted Logistic Regressive Deep Convolution Neural learning Based Feature Extraction (MWLRDCNL-FE) model is introduced in order to reduce the complexity of feature extraction during the process of liver tumor detection. Weighted Logistic Regression Analysis is a useful tool for feature selection in machine learning where the weight of each feature is determined by the magnitude of its coefficient value. A larger weight value indicates that the feature has a greater impact on the predicted outcome. The designed MWLRDCNL-FE technique includes two main processes. During the first task, Feature Extraction is performed in convolution layer where it identifies the number of features from input MRI liver images. During the second task, feature selection is performed in max-pooling layer using weighted logistic regression concept to discover the most significant features (i.e. morphological, texture, density features) from input MRI liver images with minimal complexity. By using weights to get feature importance in logistic regression proposed MWLRDCNL-FE model improves the features extraction performance of liver tumor detection with lesser time consumption. The experimental evaluation of proposed MWLRDCNL-FE model is performed by considering metrics such as feature extraction accuracy, feature extraction time, false positive rate with respect to different number of input images...
**Keywords:** Deep Convolution Neural Network, Feature Importance, MRI liver images, Tumor, Weighted Logistic Regression Analysis.

## INTRODUCTION

Magnetic Resonance Imaging (MRI) has become an important tool for doctors to diagnose liver cancer for decays. The liver is a large, granularly essential organ in the human body. The unusual lifestyle of humans caused different diseases. Because of these diseases, liver cancer has become the most prevalent cancer in many regions of the world. Liver cancer and tumors are one of the leading causes of death among other diseases across the globe. The survival rate of liver cancer patients can be significantly improved by an early diagnosis. An accurate and quick diagnosis depends on the doctor's experience and skill in analysis. Most doctors could not diagnose properly due to unidentified properties of the liver and tumors. These unspecified properties include liver and tumor size and shape and one of the most promising reasons for misdiagnosis is the quality of imaging modalities. Magnetic resonance imaging produces clearer images compared to a CT scan. In instances when doctors need a view of soft tissues, an MRI is a better option than x-rays or CTs. MRIs can create better pictures of organs and soft tissues, such as torn ligaments and herniated discs, compared to CT image. Hence, liver MRI image is taken as input. In order to enhance the performance of feature extraction from liver MRI image for tumor detection with higher accuracy, a novel MWLRDCNL-FE model is intended in this work.

Hybridized Fully Convolutional Neural Network (HFCNN) method was implemented in [1] to extract features of medical images and thereby enhances the accuracy of identifying liver tumors. However, the existing HFCNN concept for liver tumor detection is slower because of their operation of max-pooling task which results in higher time complexity. Besides to that, DenseNet Convolutional Neural Network (DCNN) was employed in [2] to improve the liver cancer diagnosis performance via extracting the features from an input image. But, the existing DenseNet CNN includes over-fitting, exploding gradients, class imbalance problems which impacts the accuracy of liver cancer prediction. An improved binary butterfly optimization algorithm was employed in [3] with the goal of finding the most relevant features during the process of liver disease diagnosis. However, this conventional

algorithm considered only medical data of liver patient where it does not obtained any images as input to predict the liver diseases.
Deep learning algorithm was utilized in [4] for efficiently recognize and categorize the liver disease by taking CT images as input. Though, the accuracy of liver cancer discovery was not adequate while giving MRI images as input. Watershed transforms and Gaussian mixture model was designed in [5] to discover diverse texture features from the segmented region. But, the optimal features were not selected for accurate liver disease diagnosis. Genetic algorithm was applied in [6] to significantly extract the features from ultrasonic images of human liver tissues. However, the false rate of optimal feature selection was higher which impacts the performance of early liver tumor detection.
A multilayer perceptron neural networks was intended in [7] with the aim of finding liver failure with the help of a liver patient dataset. This existing model employed back-propagation algorithm and thus increases the diagnosis rate and discovers the liver failure. Though, the complexity was calculated during the process of liver failure identification was not minimal. Multi-scale intermediate multi-modal fusion model was presented in [8] with the intention of performing liver tumor recognition process. But, the feature extraction performance was not satisfactory to achieve minimal false rate. Three-dimensional (3-D) CNN was implemented in [9] to perform tissue classification using MRI images and to significantly predict the primary and metastatic liver tumors. However, the ratio of number of patients that are correctly predicted as normal or liver tumor was lower.

## 2. LITERATURE SURVEY

The multi-modal guided local feature fusion concept was employed in [10] to extract the tumor features and thereby find the significant local features within the liver. Though, the feature extraction accuracy was lower to improve the early discovery performance of liver tumor. A computer aided kernel based support vector machine (SVM) algorithm was constructed in [11] for detecting the presence of liver cancer in premature stage using the patients' MRI images. In the state-of-the-art SVM concept, the histogram-based feature extraction was performed to find feature information from each MRI image. But, the ratio of number of features that are wrongly extracted as significant was more. Multi-View Feature Transformation was presented in [12] to boost the performance of Computer-Aided Diagnosis of Liver Cancers with the support of Ultrasound Images. However, the feature extraction from MRI liver was not considered.
PSO-based optimized SVM was developed in [13] to enhance the feature selection efficiency during the processes of computer-aided decision-making for locate liver disease accurately. Though, computational complexity was estimated during feature selection was very higher. Atrous Spatial Pyramid Pooling (ASPP) was planned in [14] with the objective of mining features and increasing range of feature extraction performance based on depth of the nested network. Though, true negative rate of feature extraction during liver tumor prediction process was more. A survey of dissimilar machine learning concepts was investigated in [15] to extract the radiomics features of tumor and healthy liver tissue in a CT images. A literature review of various machine learning based liver disease identification techniques were analyzed in [16] with their pros and cons to further enhance the prediction performance.
An end-to-end system with 2D and 3D convolutional neural networks algorithm was applied in [17] with the goal of quickly recognizing and segmenting tumors and to mine the metabolic information in FDG-PET/CT scans. But, the selecting the vital features to enhance the early tumors diagnosis performance with lesser complexity was remained open issue. Grey Wolf-Class Topper Optimization (GW-CTO) algorithm was presented in [18] to raise the efficiency of liver tumor diagnosis through the optimal feature selection using objective function. However, the precision of tumor discover was impacted while considering the MRI images as input. Feature extraction-based liver tumor classification was done in [19] by application of machine learning and deep learning algorithms using CT images as input. Though, higher accuracy was not estimated during the prediction of liver cancer. SVM based classifier-soft computing model was employed in [20] to increase the performance of classification of liver tumor with input CT image by considering the feature variation. But, the feature extraction accuracy was not better while getting the MRI liver images as input. Machine-learning based hybrid-feature analysis was performed in [21] for liver cancer categorization by considering the both MRI and CT Images as input. However, the number of features that are mistakenly extracted as significant using this conventional concept was higher. With the motivation of addressing the above analyzed problem during the feature extraction of liver cancer identification, a new MWLRDCNL-FE model is planned in this work.

## 3. MULTILAYER WEIGHTED LOGISTIC REGRESSIVE DEEP CONVOLUTION NEURAL LEARNING BASED FEATURE EXTRACTION

Misdiagnosed liver disease occurs because of the absent cancer symptoms during early stages which exposes patients to risks for their health. The discovery of liver disease at earlier stages requires immediate resolution to provide suitable medical interventions which protect the organ from severe damage. During liver cancer analysis the main function belongs to feature extraction. The main objective of this procedure consists of determining essential features along with discarding those without value. All features obtained from extraction proved unequal in their ability to predict liver cancer. The research introduces the MWLRDCNL-FE model which employs feature extraction through Multilayer Weighted Logistic Regressive Deep Convolution Neural learning to detect liver failure at its initial stages effectively. This work develops the MWLRDCNL-FE algorithm through the combination of weighted logistic regressive analysis with deep convolutive neural learning algorithm. The MWLRDCNL-FE model serves to detect liver cancer disease at its early stages by analyzing MRI images efficiently. The typical deep convolutive neural learning approach used for liver cancer identification operates at reduced speed because of its max-pooling functionality. This extraction methodology requires longer computational time when treating MRI liver images as entry. Using weighted logistic regressive analysis in max-pooling layer helps the proposed MWLRDCNL-FE model reduce the required time necessary to extract vital features from an input MRI liver image.. The architecture representation of proposed MWLRDCNL-FE model is demonstrated in Figure 1.

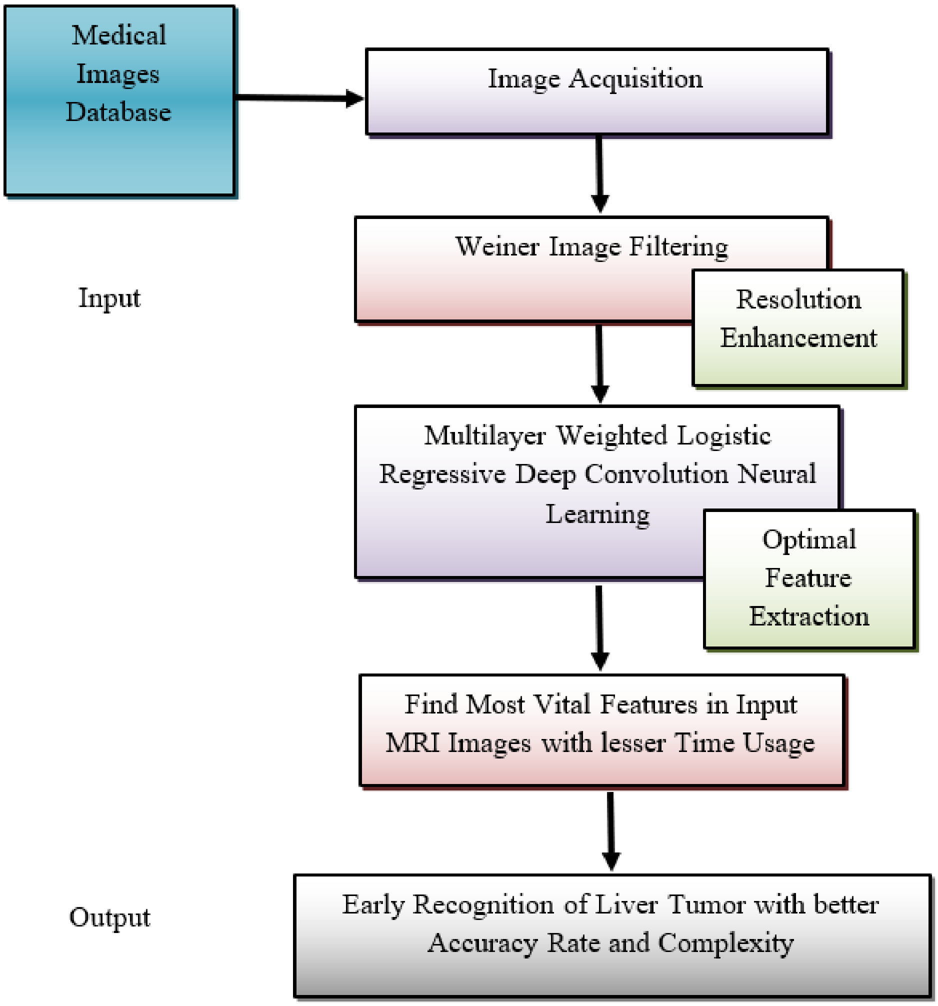


**Figure 1 Architecture of MWLRDCNL-FE Model for Efficient Feature Extraction from MRI Liver Images**

Figure 1 displays overall functions of MWLRDCNL-FE Model to enhance the performance of feature extraction from an input MRI liver image during the disease diagnosis process. As exposed in the architecture drawing, a MWLRDCNL-FE Model contains three significant tasks. At the start, image acquisition process is carried out in MWLRDCNL-FE Model in which huge size of medical database (i.e. Duke Liver Dataset (MRI) v2) is taken as input. An input database comprises larger number of Magnetic Resonance Imaging (MRI) of liver that are assumed as input. After that, wiener image filtering is utilized in MWLRDCNL-FE Model to acquire higher quality of liver MRI images for disease diagnosis. Then, MWLRDCNL-FE Model designs a novel feature extraction technique (i.e. MWLRDCNL) by combining the weighted logistic regressive analysis in deep convolutive neural learning algorithm. The proposed MWLRDCNL-FE Model improves the feature extraction accuracy of MRI liver images with lesser time complexity via assigning the weight to each extracted features according to their magnitude of its coefficient value. In MWLRDCNL-FE Model, higher weight value point outs that the feature includes a greater impact on the predicted result (i.e. liver tumor diagnosis). From that, MWLRDCNL-FE Model predicts only most significant features that are presented in given MRI liver images for recognition of liver cancer effectively.

### 3.1 Image Acquisition

The primary function of MWLRDCNL-FE Model is image acquisition. The goal of image acquisition process is to acquire the image of required part or effected area so that the prediction of liver cancer can be performed. This process begins with gathering MRI images of liver of different person from the record or available data base. These MRI liver images are further considered as input to the system**.** In MWLRDCNL-FE Model, more of liver MRI images obtained as input from a Duke Liver Dataset (MRI) v2 and which are described as '$MDB = LI_1, LI_2, .., LI_k$'. An MRI reveals the structure of the liver, different growths and information about the size of the cancer.

### 3.2 Image Resolution Enhancement

The second function of MWLRDCNL-FE Model is an image resolution enhancement where it increases the quality of MRI liver images through removing all the noisy pixels. This process gives a clear better and the accurate features of the desired region. The noise in input MRI liver images may give wrong disease diagnosis results. Moreover that the noise may give the false information regarding the tumor and thus the patient is misguided. Therefore, the removal of noise is essential. Wiener image filtering is employed in MWLRDCNL-FE Model for eliminating noise from input MRI liver images without blurring edges. For that reason, Wiener image filtering is appropriate for increasing the resolution of MRI liver images. The process of wiener image filtering based resolution enhancement is demonstrated in Figure 2.

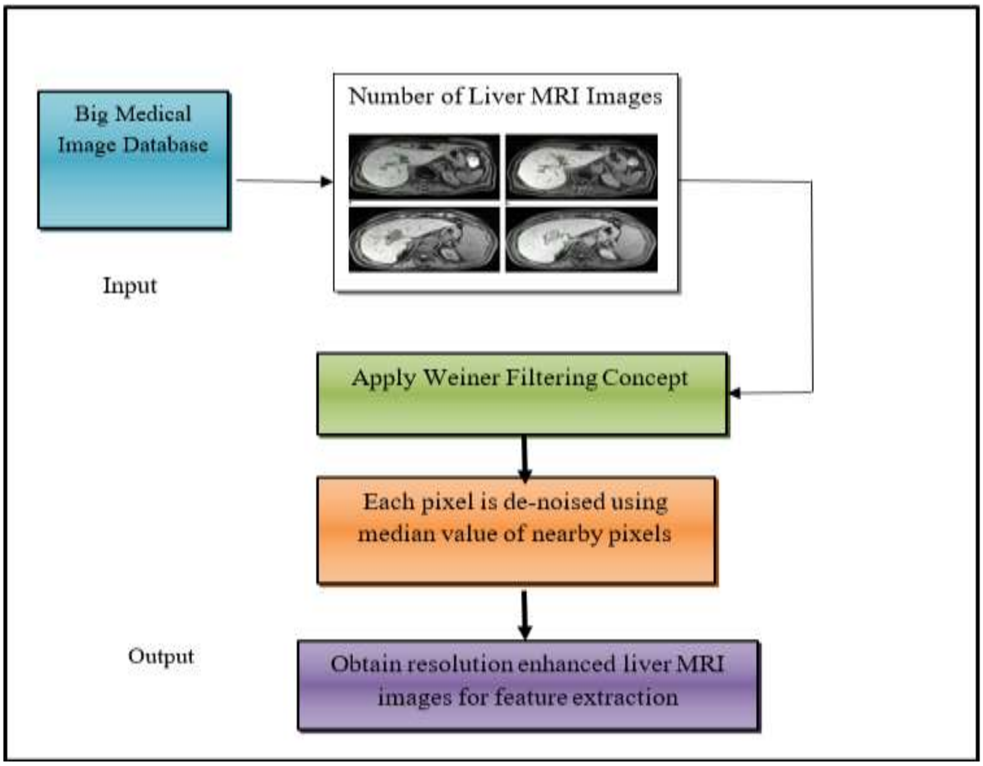


**Figure 2 Images Resolution Improvement Using Weiner Filtering**

Figure 2 demonstrates the block diagram of image resolution enhancement. As presented in above process, at first Weiner filtering is utilized in MWLRDCNL-FE Model gets large medical database '$MDS$' as input where it contains more number of liver MRI images '$LI_1, LI_2, .. LI_Z$'. Here, '$z$' defines a total number of MRI liver images presented in an input database. A wiener filter in MWLRDCNL-FE Model is an adaptive i.e. it can adjust to the dynamic attributes of the input signal and the noise signal. This can formulate it appropriate for applications where the signal and noise statistics are unknown or change over time i.e. speech enhancement, image restoration, or radar discovery. In the MWLRDCNL-FE Model, it assumes each pixel of a liver MRI image in sequence order and considers its near pixel to make a decision i.e. whether or not it is representative of its surroundings. Rather than changing the pixel value with the mean of near pixel values, wiener filter changes it with the median of those values. From that, Wiener image filtering is mathematically done using following equation,

$$w(u_1, v_2) = \frac{H*(u_1,v_1)p_x(u_1,v_1)}{H(u_1,v_1)^2 p_x(u_1,v_1)+p_n(u_1,v_1)} \quad (1)$$

Using equation (1), wiener filter in MWLRDCNL-FE Model efficiently removes the additive noise and blurring in given MRI liver images. The core benefits of utilizing a wiener filter for noise minimization in MWLRDCNL-FE Model as where it optimal in mean square error i.e. lessens the expected value of the squared error signal. This process results in quality enhanced output that protects the signal attributes and decreases the noise effects.

**3.3 Optimal Feature Extraction**

Considering the more number of input features can negatively impacts the recognition performance of liver tumor because high numbers of attributes may lessens the classification accuracy due to the redundancy or insignificance of some attributes. For that reason, feature selection is an essential task in finding the most useful features and for tuning the classifier's performance to exactly classify the patient's medical data. Thus, feature extraction and selection is a considerable problem to be resolved in cancer diagnosis to enhance performance of classification. In this proposed research methodology, Multilayer Weighted Logistic Regressive Deep Convolution Neural learning (MWLRDCNL) concept is designed. The novel MWLRDCNL is proposed with the assist of Weighted Logistic Regressive Analysis (WLRA) and Deep Convolution Neural Network (DCNN). By the application of WLRA and DCNN, proposed MWLRDCNL efficiently detects and also extracts only most vital features in input MRI liver images with minimal amount of time utilization. The implemented MWLRDCNL comprises more benefits in optimal feature extraction process due to its convolution and max-pooling functions. The MWLRDCNL finds the imperative features in input MRI liver images without human involvement. The process of MWLRDCNL is displayed in Figure 3.

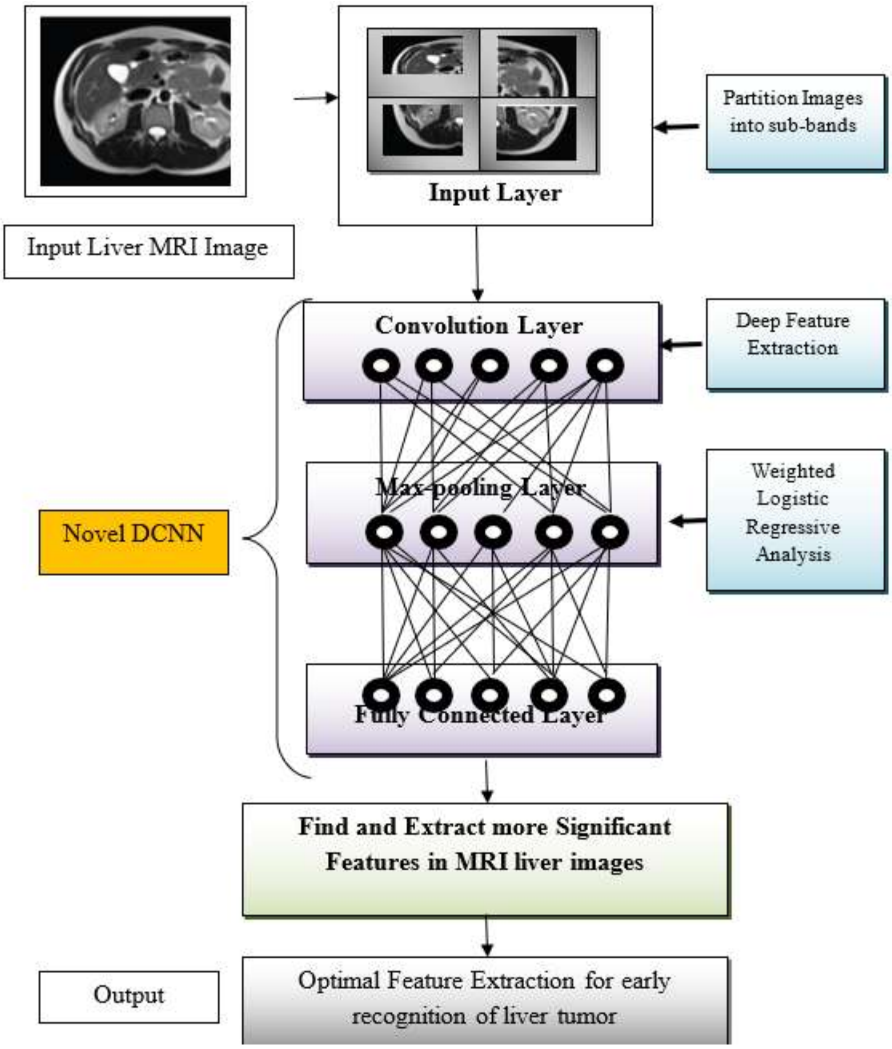


**Figure 2 Block Diagram of MWLRDCNL for Optimal Features Extraction**

Figure 2 shows the exhaustive processes of MWLRDCNL to decreases the time complexity of optimal features extraction. The MWLRDCNL initially assumes 10-layer DCNN architecture. Then, MWLRDCNL gets number of liver MRI images '$LI_i = LI_1, LI_2, .., LI_k$' in given database as input. In MWLRDCNL, convolution layer deeply learns and mines the all features that are presented in input liver MRI of each patients with help of below equation,

$$Convol^z(LI_i, j) = \omega t^{z,l}(u, v).input^{LI_i}(LI_i - u, j - v) + bi^{z,l} \quad (2)$$

In above equation (2), '$\omega t^{z,l}$' represents $z^{th}$kernel and '$bi^{z,l}$' defines the bias of $z^{th}$ layer. The outcomes of the convolution layer is linked with a max-pooling layer where it minimizes the dimensionality of features with the application of WLRA by means of extracting the most vital features in images with aid of below formulation,

$$Output^z(LI_i, j) = tanh\big(Convol^z(LI_i, j)\big) \quad (3)$$

In the above equation (3), $tanh$ describes an activation function in which MWLRDCNL utilizes WLRA concepts with aiming at lessening the features dimensionality to enhance the performance of early identification of liver cancer. The outcomes of convolution layer in MWLRDCNL i.e. deep features learning process are explained mathematically as,

$$f_i = f_1, f_2, .., f_n \quad (4)$$

Followed by, MWLRDCNL applies WLRA in max-pooling layer in order to discover the most useful features (i.e. morphological features, texture features, density features) in input liver MRI images. Here, 'n' describes the number of extracted features. On the contrary to state-of-the-art works, WLRA employed in max-pooling layer considers feature importance i.e. calculates the weight for all input features and thereby determines the importance of each feature in the decision-making process. The higher the weight for a feature, the larger effect it has on the model to recognize the liver tumor disease. The WLRA is a statistical algorithm where it analyzes the association between two data factors (i.e. independent variables and dependent variables). The WLRA acquired independent variables (i.e. extracted features) as input and gives result as a probability value between 0 and 1. Here, the dependent variable represents the liver tumor disease symptoms. The input independent variables i.e. extracted features is mathematically defined as,

$$F = \begin{bmatrix} f_{11} & \cdots & f_{1m} \Big| & \Big| f_{nm} \Big| & \Big| \\ f_{12} & \cdots & f_{2m} \cdots & & \\ \cdots & \cdots & & & \end{bmatrix} \quad (5)$$

Subsequently, the WLRA task of max-pooling layer is mathematically represented as,

$$Y = (\textstyle\sum_{i=1}^{n} w_i f_i) + c \quad (6)$$

In equation (7), '$f_i$'depicts the $i^{th}$observation of 'F' and '$w_i = w_1, w_2, .. w_m$' is the weight or coefficient whereas 'c' illustrates the bias term. The above mathematical expression of WLRA process is simply expressed as,

$$Y = w.F + c \quad (7)$$

Here, dependent variable 'Y' includes only binary value i.e. 0 or 1. The WLRA process in max-pooling layer results in either '0' or '1' in which '1' describes that an input features are highly related to predicted results and '0' defines that an input features are not related to predicted results. With the support of WLRA, max-pooling layer gives weight value '0' or '1' to each extracted features from convolution layer and thereby discover feature significances. From that, MWLRDCNL mines a feature which contains a higher weight value as more useful features for early forecasting of liver cancer with minimal amount of time requirement.

The pseudocode representation of MWLRDCNL-FE Model is shown as follows,

| **Multilayer Weighted Logistic Regressive Deep Convolution Neural learning Based Feature Extraction Model** |
|---|
| **Input:** Number of MRI liver images in Medical Database $MDB = LI_1, LI_2, .., LI_k$'; |
| **Output:** Attain higher feature extraction accuracy and minimal time complexity for liver cancer analysis |
| **Step 1:Begin** |
| **Step 2:** **For** each liver MRI image '$LI_i \in MDB$' |
| **Step 3:** Apply Weiner filtering concept |
| **Step 4:** De-noise pixels in input liver MRI image '$LI_i$' using (1) |
| **Step 5:** Give resolution enhanced liver image for feature extraction |
| **Step 6:** **For** each resolution improved liver image |
| **Step 7:** Apply MWLRDCNL concept |
| **Step 8:** gets number of '$LI_i$' as input and partition it into sub-bands |
| **Step 9:** Convolution layer deeply extracts number of features in input '$LI_i$' using (2) |
| **Step 10:** Max-pooling applies WLRA using (6) |
| **Step 11:** Assign weight to each features |
| **Step 12:** Selects features with higher weight as significant features using () |
| **Step 13:** Return only most importance features for tumor prediction |
| **Step 14:** **End For** |
| **Step 15:** **End For** |
| **Step 16: End** |

**Algorithm 1 Multilayer Weighted Logistic Regressive Deep Convolution Neural Learning Based Feature Extraction**

### 3.3 SIMULATION BACKGROUNDS

With the purpose of analyzing the performance of feature extraction during the liver tumor identification process, proposed MWLRDCNL-FE Model and existing Hybridized fully convolutional neural network (HFCNN) method [1] and DenseNet convolutional neural network (DCNN) [2] are implemented in MATLAB. The Duke Liver Dataset (MRI) v2 from (https://zenodo.org/record/7774566) taken as input to conduct the simulation for both the proposed and existing two techniques where it encompasses 310 distinctive image series. Thus, varying numbers of testing liver MRI images in the range of 30 to 300 are gathered as input to perform simulation task. The outcome of proposed MWLRDCNL-FE Model is compared with the state-of-the-art HFCNN [1] and DCNN [2]. The implementation result of proposed MWLRDCNL Model is validated using following testing parameters such as feature extraction accuracy, feature extraction time and false positive rate.

### 4.1 Testing Scenario 1: Feature Extraction Accuracy

Feature Extraction Accuracy '$FEA$' of liver tumor analysis is determined based on the ratio of number of liver images with accurately extracted features as significant to the total liver images obtained as input to accomplish the simulation evaluation. As a result, feature extraction accuracy of liver cancer recognition is mathematically computed with the aid of below formula,

$$FEA = \frac{NLI_{CEVF}}{k} * 100 \qquad (8)$$

In equation (8), '$NLI_{CEVF}$' defines number of input liver MRI images with correctly extracted vital features whereas '$k$' illustrates total input images get as input for carried outing the implementation. The accuracy during the feature extraction process is estimated in percentage (%).

**Table 1 Comparative Performance of Feature Extraction Accuracy**

| Number of Input Liver MRI Images | Feature Extraction Accuracy (%) | | |
|---|---|---|---|
| | HFCNN | DCNN | MWLRDCNL-FE Model |
| 30 | 77 | 86.22 | 92 |
| 60 | 78.11 | 86.57 | 92.34 |
| 90 | 78.59 | 87.04 | 92.67 |
| 120 | 79 | 87.63 | 93 |
| 150 | 80.16 | 88.75 | 93.40 |
| 180 | 81.48 | 89 | 93.95 |
| 210 | 83.55 | 89.82 | 94.44 |
| 240 | 84.06 | 90.46 | 94.72 |
| 270 | 85.71 | 91.30 | 96.41 |
| 300 | 87.94 | 92 | 97.03 |

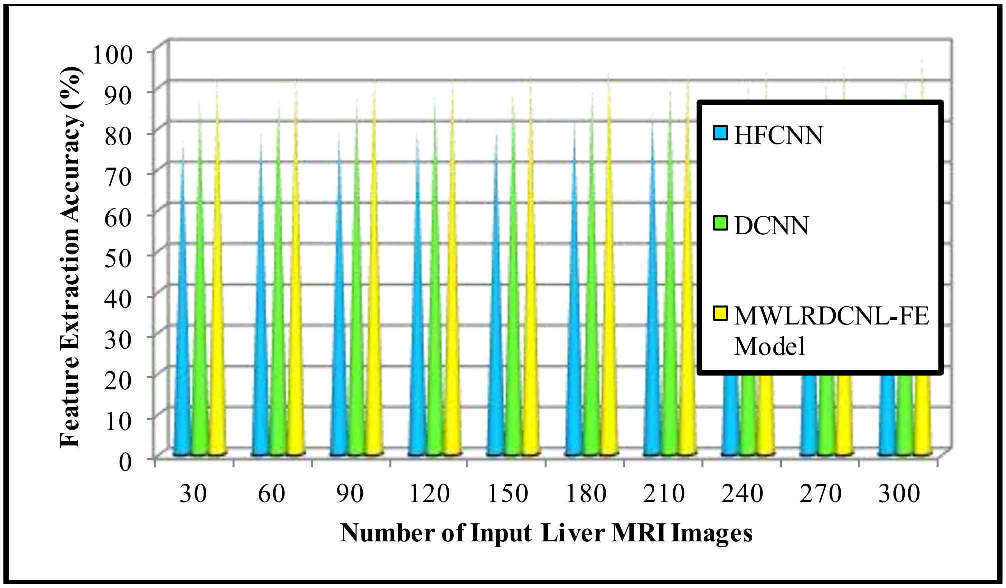


**Figure 4 Graphical Results of Feature Extraction Accuracy for Liver Tumor Recognition**

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Table 1 and Figure 4 presents the tabulation and graphical results comparison of feature extraction accuracy for detecting liver tumor disease at early stage by considering a different number of input liver MRI images using three research methodologies. As displayed in above performance analysis, proposed MWLRDCNL-FE Model get enhanced accuracy for detecting the most significant features in testing images as input when compared to state-of-the-art HFCNN [1] and DCNN [2]. Improved feature extraction accuracy is obtained in proposed MWLRDCNL-FE Model due to the application of novel DCNN concepts and WLRA on the contrary to existing diagnostic algorithm. By the support of WLRA, MWLRDCNL-FE Model mines only most useful features for predicting the liver tumor disease. As a result, the MWLRDCNL-FE Model increases the ratio of number of liver images with accurately extracted features as most significant when compared to conventional works. When getting a 270 liver MRI images from Duke Liver Dataset (MRI) v2 as input, MWLRDCNL-FE Model achieved 96.41 % feature extraction accuracy whereas existing HFCNN [1] and DCNN [2] gained 85.71 %, 91.30 % respectively. Thus, the MWLRDCNL-FE Model gives better feature extraction accuracy for enhancing the liver tumor diagnosis performance when compared to state-of-the-art works.

**4.2 Testing Scenario 2: Feature Extraction Time**

Feature Extraction Time '$FE_{time}$' of the liver cancer diagnosis is estimated based on the total amount of time used in order to correctly extract the key features in an input liver MRI images. Accordingly, time complexity of feature extraction is mathematically computed using following equation,

$$FE_{time} = k * time(CEVFSI) \quad (9)$$

In the mathematical formula (9), '$time(CEKFSI)$' describes a time taken for correctly extracting the vital features in single liver MRI images whereas '$k$' point outs the number of MRI images acquired as input during the experimental work. The time complexity during the feature extraction process of liver cancer prediction is calculated in milliseconds (ms).

**Table 2 Comparative Performance of Feature Extraction Time**

| Number of Input Liver MRI Images | Feature Extraction Time (ms) | | |
|---|---|---|---|
| | HFCNN | DCNN | MWLRDCNL-FE Model |
| 30 | 15.9 | 14.1 | 10.7 |
| 60 | 18.4 | 16.5 | 12.3 |
| 90 | 20 | 18.3 | 14.5 |
| 120 | 22.3 | 21.1 | 16 |
| 150 | 24.6 | 23 | 18.4 |
| 180 | 26.9 | 25.4 | 20.9 |
| 210 | 31.5 | 27.6 | 22.8 |
| 240 | 32.8 | 28.8 | 25.1 |
| 270 | 34.9 | 31.7 | 27.4 |
| 300 | 37.3 | 33.4 | 30 |

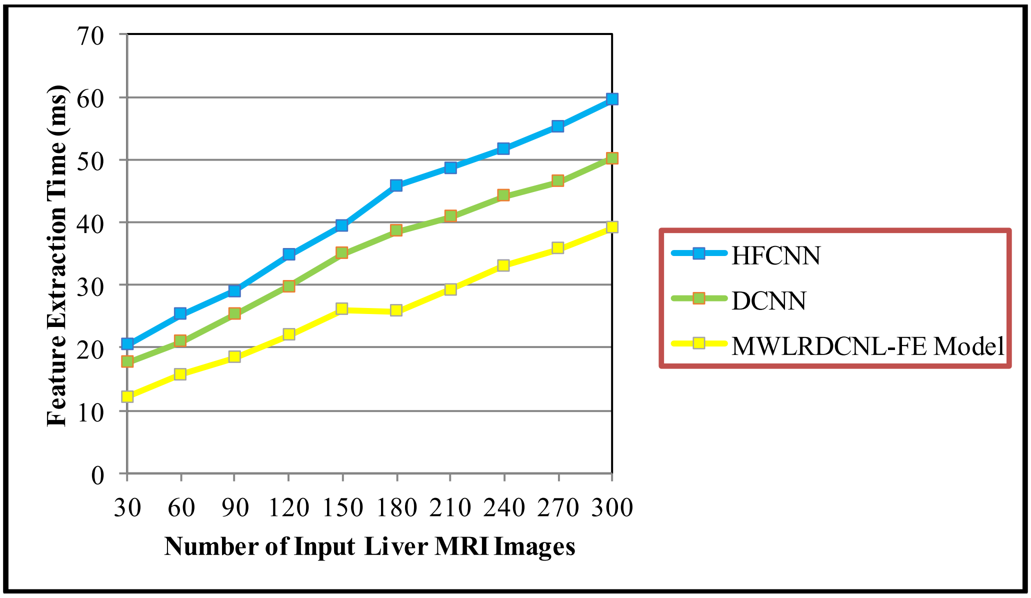


**Figure 5 Graphical Results of Feature Extraction Time for Liver Tumor Analysis**

Table 2 and Figure 5 describes the performance results of time complexity is estimated during the feature extraction processes of liver tumor analysis with respect to varied number of input liver MRI images in the range of 30-300 using three research methodologies. As shown in the above obtained results, proposed MWLRDCNL-FE Model acquired lesser computational complexity for optimal feature extraction process while taking more number of input images as input when compared to conventional HFCNN [1] and DCNN [2]. The better time complexity is estimated in proposed MWLRDCNL-FE Model which owing to the utilization of WLRA in DCNN concepts on the contrary to conventional algorithms. The MWLRDCNL concept is introduced in proposed work enhances the features extraction performance for achieving better disease diagnosis rate with lesser time. For that reason, the proposed MWLRDCNL-FE Model lessens the time needed in order to correctly find and extract most important features from in an input liver MRI images when compared to existing HFCNN [1] and DCNN [2]. When assuming 150 liver MRI images as an input, proposed MWLRDCNL-FE Model gets 18.4 ms time complexity for optimal feature extraction whereas conventional HFCNN [1] and DCNN [2] obtained 24.6 ms, 23 ms respectively. Accordingly, the proposed MWLRDCNL-FE Model attained lesser time complexity for early tumor analysis when compared to conventional diagnostic algorithms.

### 4.3 Testing Scenario 3: False Positive Rate

False Positive Rate '$Fal_{PR}$' of features extraction is determined based on the ratio of number of liver MRI images with inaccurately extracted features as vital or significant to the total number of images assumed as input to perform the simulation. The false rate of feature extraction during the liver cancer analysis is mathematically measured as,

$$Fal_{PR} = \frac{NLI_{IEVF}}{k} * 100 \qquad (10)$$

In the mathematical description (10), '$NLI_{IEVF}$' illustrates number of liver MRI images with wrongly extracted features as vital and '$k$' refers total number of input images. The false positive rate of feature extraction during the liver tumor identification process is measured in percentage (%).

**Table 3 Comparative Performance of False Positive Rate**

| Number of Input Liver MRI Images | False Positive Rate (%) | | |
|---|---|---|---|
| | **HFCNN** | **DCNN** | **MWLRDCNL-FE Model** |
| 30 | 23 | 13.78 | 8 |
| 60 | 21.89 | 13.43 | 7.66 |
| 90 | 21.41 | 12.96 | 7.33 |
| 120 | 21 | 12.37 | 7 |
| 150 | 19.84 | 11.25 | 6.6 |
| 180 | 18.52 | 11 | 6.05 |
| 210 | 16.45 | 10.18 | 5.56 |
| 240 | 15.94 | 9.54 | 5.28 |
| 270 | 14.29 | 8.7 | 3.59 |
| 300 | 12.06 | 8 | 2.97 |

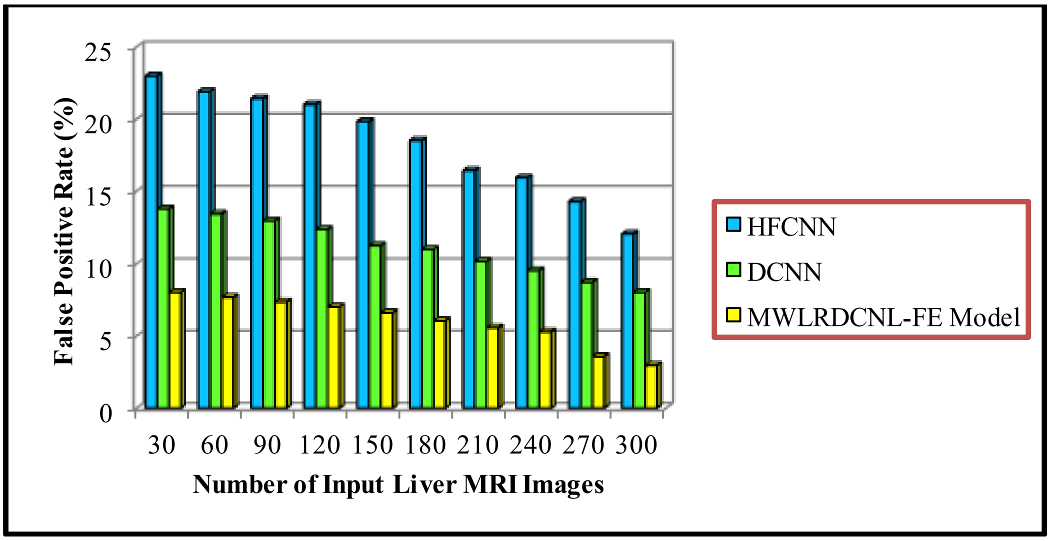


**Figure 6 Graphical Results of False Positive Rate for Liver Tumor Prediction**

Table 3 and Figure 6 depicts the simulation results of false positive rate is calculated during the optimal feature extraction process for boosting the performance of liver cancer detection at an early stage using three model depends on various number of input liver MRI images in the range of 30 to 300. As demonstrated in the above graphical diagram and tabulation results, proposed MWLRDCNL-FE Model gained better false positive rate while assuming larger number of input images as compared to existing HFCNN [1] and DCNN [2]. The minimum false rate is acquired during the optimal features extraction and selection task in proposed MWLRDCNL-FE Model which because of the employment of WLRA and DCNN concepts. The WLRA is utilized in proposed MWLRDCNL-FE Model helps to find the feature importance and thereby it improves performance of key feature extraction. For this cause, the proposed MWLRDCNL-FE Model lessens the ratio of number of liver MRI images with inaccurately extracted features as vital or significant when compared to conventional research works. When obtaining 210 liver MRI images as an input for implementation, proposed MWLRDCNL-FE Model gets 5.56 % false positive rate whereas existing HFCNN [1] and DCNN [2] obtained 16.45 %, 10.18 % respectively. From that, the proposed MWLRDCNL-FE Model presents better false rate for efficient liver tumor analysis when compared to state-of-the-art works.

## 5. CONCLUSION

In this article, a novel MWLRDCNL-FE Model is presented in order to significantly enhance the efficiency of feature extraction and selection during the liver tumor diagnosis process. The motivation of MWLRDCNL-FE Model is achieved with the utilization of new WLRA concept in DCNN on the contrary to conventional research works via introducing an optimal feature extraction concept. The proposed MWLRDCNL-FE Model helps for physician and radiologist to effectually recognize liver tumor diseases of a patient at a premature stage with higher feature extraction accuracy. Furthermore, MWLRDCNL-FE Model decreases time complexity taken to accurately find and extracts the more valuable features in input MRI images by considering the feature importance where it give a weight to input features based on how useful they are at predicting liver tumor diseases. Likewise, MWLRDCNL-FE Model lessens the false positive rate of feature extraction with the support of WLRA because where it extracts only features which include a higher weight as most significant for tumor analysis. The experimental outcomes verified that the proposed MWLRDCNL-FE Model presents better liver tumor identification performance with higher feature extraction accuracy and lesser time complexity and false positive rate when compared to state-of-the-art algorithms...

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