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Binary Classified Convolutional Neural Network Model for Liver Cancer Tissue Identification at Early Stages

Ankita[1] and Kamal Malik[2]
[1]Research Scholar, Department of Computer Science, CT University Ludhiana, Punjab
[2]Professor, Department of Computer Science, CT University Ludhiana, Punjab

Abstract. Cancer is the abnormal growth of cells in a particular part of a body which forms lumps. These lumps are commonly called tumours. Liver cancer is a deadly and aggressive disease that grows rapidly in the body. Diagnosis of liver cancer with early detection and high accuracy can improve patient survival time. Histopathological image analysis is time-consuming and ambitious to manually detect cancer cells. In this work, a methodology is applied to PET – CT images which help to identify cancer cells as well as predict prognosis. First, a median image filter is applied to eliminate noise from the input CT images before applying them to the model. In this paper, a trained ConvNet model is implemented to classify a patient's liver tumour. Deep learning resolves the complex problem and challenge of cancer recognition using neural networks. Nevertheless, deep learning is a powerful technique which uses neural networks to enable the classification of abdominal hepatic lesion images. This model partially solves the dimensionality problem. For this proposed model, CT images of 214 liver patients were collected and the data was split in the 80:20 ratios for training and testing. The model achieves a classification accuracy of 95.35% with a validation loss of 0.20% using a deep learning-based CNN model.
Keywords – CT images, Liver Lesion, Median Filter and Convolutional Neural Network.

1. Introduction

Our body is made up of trillions of cells. When these cells become old, they die on their own and produce new cells as per the requirement of the body[1],[2]. However, if the dead cells regrow and form new cells, these cells are commonly referred to as tumours[3]. A tumour can be cancerous (malignant) or non–cancerous (benign)[4]. In contrast, a benign tumour is large but it is neither metastatic nor harmless. Malignant tumours are metastatic tumours that travel to the bloodstream and lymphatic system[5]. These harmful tumours are commonly found in the lungs, liver, bone and brain.The Liver is a sanctuary where cancer cells migrate to the liver[6], [7]. This is usually known as liver cancer. It is generally of two types, primary liver cancer and secondary liver cancer, also called metastatic or metastasized cancer which describes cancer that has spread to the liver through some other organs of the body [8], [9]. Primary liver cancer is classifying the cells of origin, which includes hepatocytes (Hepatocellular Carcinoma, Fibrolamellar Carcinoma, Hepatic adenoma, Hepatoblastoma), blood vessels (Angiosarcoma, cholangiocarcinoma, Hemangioendothelioma, Fibro sarcoma, Leomyosarcoma and Rhabomyosarcoma) and germ cells (Teratoma, Yolk Sac tumour, Lymphomas).With this intention, early handling of liver cancerous nodules is substantial. In the initial stage, the patient has some symptoms and the patient is suffering from serum hepatitis, Non-alcoholic fatty liver (NAFLD), steatohepatitis (Alcoholic liver) etc[10], [11]. For these reasons, the risk of cancer in the liver may increase.The disease can be cured or treated by a gastroenterologist if detected at an early stage [12]. Data from 1990 to 2020 is recorded and examined in Table 1 to show that patients with chronic hepatitis B and C are at higher risk of cancer cells in the liver.

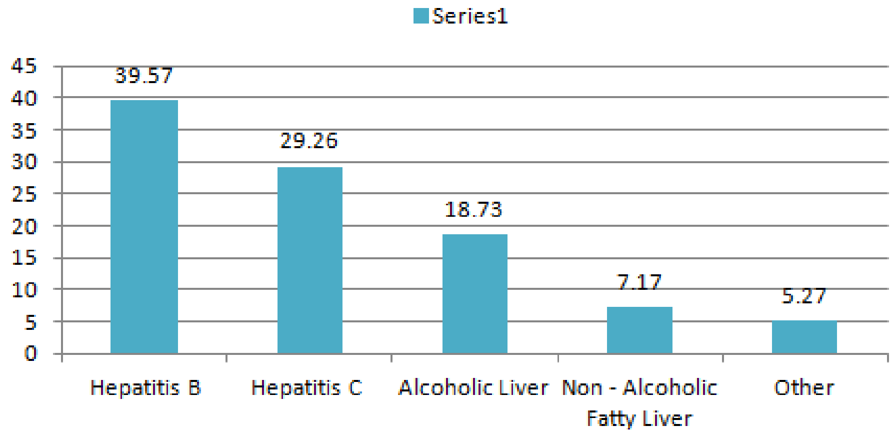


Table 1. Risk factors of liver cancer patients from 1990 to 2020

The doctors can recommend different modalities like MRI, CT, PET, mammography and ultrasound to point out the malady and to estimate the anomalies in human organs. Of this, a CT scan is the most normally manipulated diagnostics technique for liver cancer detection[13], [14], [15]. In this research, around 300 CT images are employed for training and testing purposes[16]. Accuracy can be negatively affected by several factors during the diagnosis of cancerous transitions, for example, radiologist tiredness and preoccupation with the sophistication of liver structure and subtle aspects of early detection of disease[15]. To solve these problems, computer-aided diagnosis helps radiologists to resolve this issue[18]. The rest of the paper looks like this: Section 1 deals with an introduction to tumour cells and liver cancer. Section 2 explains the various artificial intelligence techniques already used by researchers to detect cancer cells. Section 3 describes the methodology used to detect the tumour in early stages and the corresponding result and accuracy are covered in section 4 of this discussion.

2. Related Work

The main intent of this study is to recognize cancerous tissue using deep learning which is considered a complicated task and time–consuming manually in the current scenario. An influential tool for semantic segmentation, a hybridized fully convolution neural network has been proposed to be modelled mathematically and resolve the existing issue of liver cancer. A texture classifier was manipulated to separate ROIs into normal and abnormal hepatic tissue. The conceptual functionalities have been used to contrast various hepatic lessons at the classification detection stage. CNN is used as a voxel classifier to accomplish subsequent segmentation of tumours. The suggested HFCNN method indicated a valid liver measurement of 97.22%[19]. This paper based on deep learning clarifies the evolution of a model that classifies expected hepatic lesions on multiphase MRI images. The ConvNet model by employing three convolutional layers was contrived by an iterative optimization of the network architecture and training cases. An improved linear activation function was capitalized for the instantaneous and adequate performance of the model. The process is passed through two pooling layers to assign the maximum value for each path of the feature map. The output from the final pooling was flattened and fed into two fully connected layers. Well-known Adaptive Moment Estimation optimizer technique is used to aid in minimizing the loss function. The Adam optimizer updates this model in response to the output of the loss function. The Adam optimizer algorithm was used to update network weights iteration. For validation, the shuffle split cross-validation method is used which can randomly split the data for training and testing. This propose neural network model exhibits 92% accuracy and sensitivity [20].

3. Methodology and Model Building

Systematic Research is conducted to address the various difficulties and problemsencountered in the detection of cancerous tissues in the liver using Convolutional Neural Network (CNN) technique by applying median filter for removing noise from the images.

3.1 Dataset of CT Images

Data gathering is the initial and crucial step in the machine learning model, which is also helpful in training, testing and validation of the model. To build this model, CT images of liver patients were collectedfrom Mayyo Imaging and diagnosis centre, Ludhiana, Punjab. These CT images of liver patients with phase difference were taken and samples of these images are shown in Fig 1. The specific method for classifying lesions from CT-Scan images is because there substantial evidence that computer-aided techniques can show valid results in comparison to other clinical diagnoses. To apply the CNN technique, CT – Scan images of 363 abnormal–functioning liver patients are amassed. Out of these 363 images, 214 images are of those patients who are suffering from liver cancer and 149 images are of other inherited liver diseases and viruses such as HBV, chronic hepatitis C, fatty liver, alcoholic or non-alcoholic fatty liver and cirrhosis. Regarding data partition, 80% of the data is used for training the model and 20% is utilised for testing the data. A large chunk of data is given for training purposes as the model should learn more from this data.

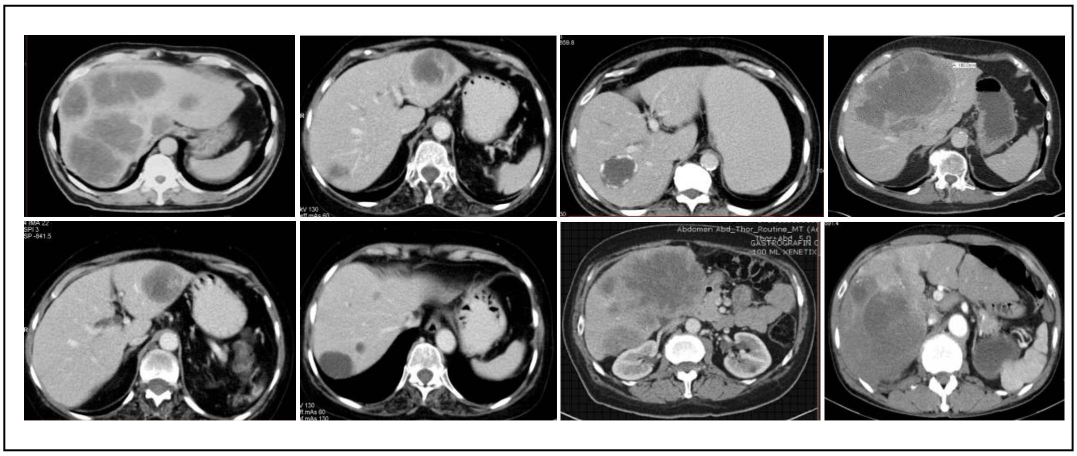


Fig. 1. Datasetofgreyscale CT images for liver cancer patients.

3.2 Image Pre-Processing

After data collection, the first step is to pre-process the data images by searching for noise inside each pixel in the images. Noise is a significant problem that usually comes up when we deal with digital image processing or apply AI techniques for further processing. This salt-and-pepper noise, as shown in Fig 2, can degrade the quality of the CT images and thus lead to the loss of important information.

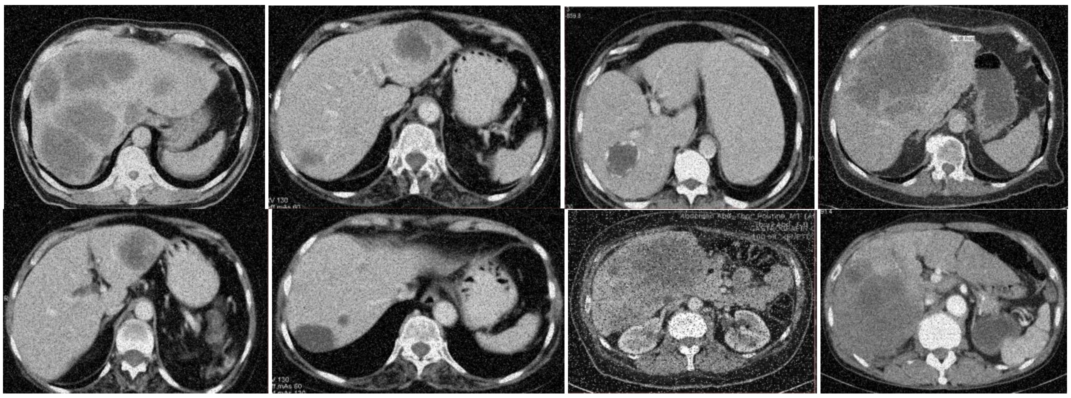
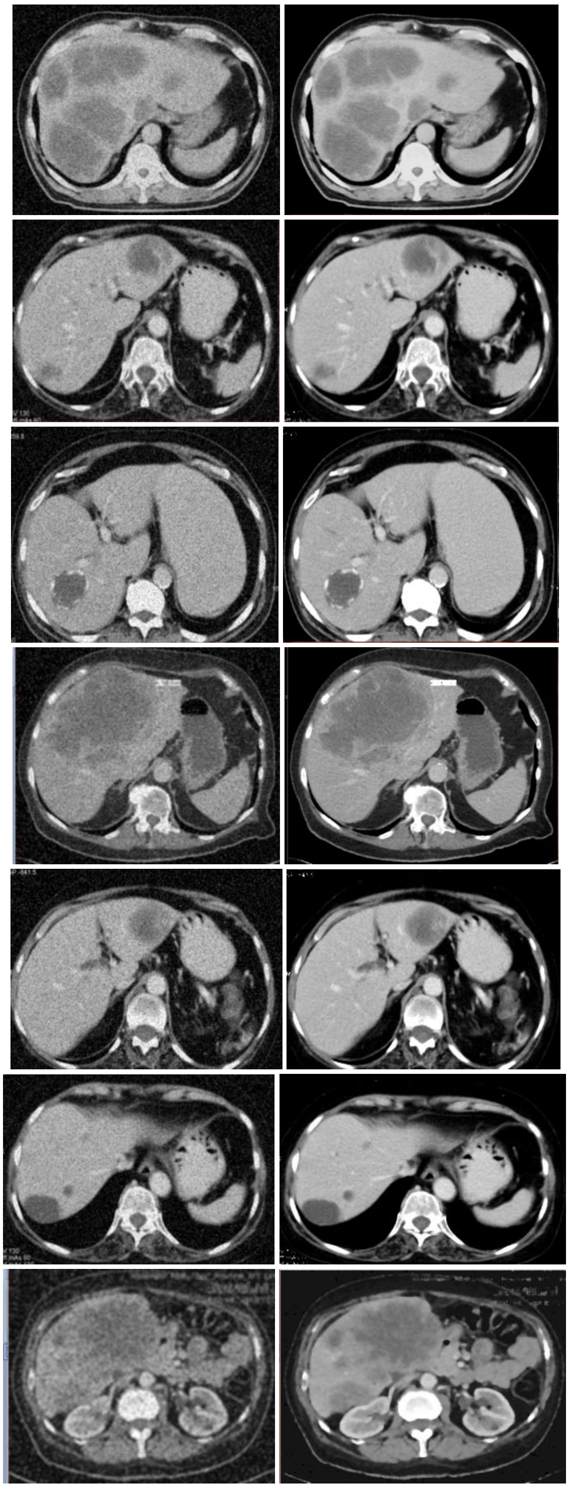


Fig. 2. Noise exists in clinical liver lesion images.

Established non-linear image filtering technique are used to remove the noise from the images before apply them directly to the model. The Median filter technique is one of best filter technique which is compared with mean filtered technique as clearly shown in Fig 3. The median filter indicates better outcomes and is helpful in vanishing luminance noise from the image. The model may directly extract the features from images by denoising from the noisy CT images which gives more accurate result in classifying the model.

Mean Filter Median filter



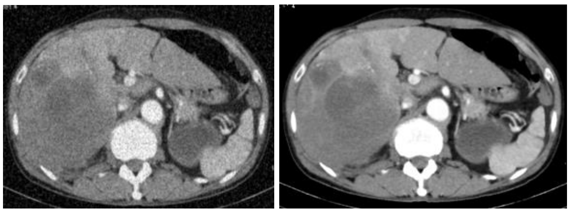


Fig. 3. Comparison between Mean and Medium denoising image Filter techniques.

3.3 ConvNet or CNN

A model based on deep learning has the efficiency to work in a multi-dimensional array. Deep learning algorithms are extensively used to flatten the CT images of liver lesion patients from a multi-dimensional array to a 1D array. This will reduce the time to train the model and reduce the memory space. It looks for different features in the Computational Tomography (CT) images of a liver in which the patient is suffering from benign, cirrhosis and malignant tumours. The data is trained so that the model can classify tumours more accurately. The model can take features instead of learning pixel values. Deep learning assigns different features or dimensions of being in an image. Furthermore, this model works better as we provide more and more amount of data. Unlike a machine learning algorithm, it reaches a threshold value. The performance and accuracy of the machine learning model will not increase as we continually feed more data to the machine learning model. Despite that, this model based on deep learning circumvents the overfitting issue of a single image as we can frequently feed more diagnosis images. It also gets additional dimensions which provide more accuracy. The problem of overfitting is another challenging task in medical images. The proposed CNN model has the potential to solve this overfitting problem in multi-texture images for classification and segmentation.

3.3.1 Network Architecture

A proposed early liver cancer detection model based on deep learning to optimize the CNN model for image classification is presented. To make training faster, a GPU – based CNN model strategy is employed. This model is a sequential model that leverages CNN to extract features from the region of interest (ROI) and describes seven–layer architecture. This seven – layers CNN architecture includes 3 convolutional layers, as well as three max–pooling layers and one fully connected layer. Within this sequential model, the first convolutional layer of this method incorporates different parameters such as filters, kernel size and non–linear activation function. The feature map value is calculated by using the following formula.

$$f'(\alpha,\beta) = (i*k)[\alpha, \beta] = \sum_m \sum_n h[m,n] f[\alpha - m, \beta - n] \quad (1)$$

As in the above formula, 'α' and 'β' are the indexes of rows and columns of the result matrix, respectively. However, 'i' implies the input image and 'k' implies the kernel. Each convolutional layer consists of convolutional filters and non–linear activation functions such as ReLu. The ReLu activation function is used instead of the squashing function or S-shape sigmoid function. A rectified linear (ReLu) transfer functioncorrected a gradient descent problem by vanishing and restricting the result. The ReLu is regarded as a typical landmark and the simplest activation function in the deep learning model, ranking higher than other linear and non–linear activation functions.The formula for the ReLu activation function describes as follows.

$$y = \begin{Bmatrix} i \geq 0, return\ x \\ i < 0, return\ 0 \end{Bmatrix} \quad (2)$$

After the derivative the equation

$$y' = \begin{Bmatrix} i \geq 0, return\ 1 \\ i < 0, return\ 0 \end{Bmatrix} \quad (3)$$

The above expression illustrated that for all input value of i if i is greater than or equal to zero then output variable y will be equals to 1 and if i is less than zero then the value of y remains 0 only. The size of the RGB image as input should be of dimension 64 X 64. It is very important to initialize the shape of the image before creating the model. Otherwise, the model suffers from the problem of overfitting.To reduce the dimensionality in the first convolutional layer, 32 discrete filters are used with a kernel size of 3 X 3. A filter can see the whole image and is not feature-specific as features are not extracted in this layer.The maximum intensity value is picked out from the convolutional layer with the help of max-pooling of size 2 X 2 as shown in Fig 4. In the second convolutional layer, the filter value is increased from 2^5 to 2^6 to extract the features from the entire image. This is called ROI. In addition to ROI, features are extracted from the image in this layer. It can extract more information from an extracted image.

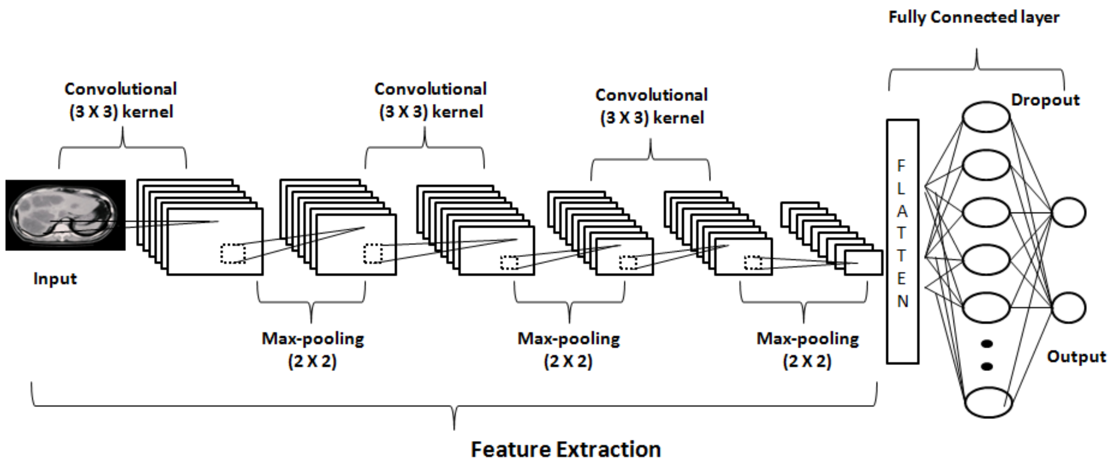


Fig 4. The Proposed Convolutional Neural Network Architecture of the model

Similarly to the previous one, the max-pooling layer is optimized with uniform size to reduce the number of computations in the neural network to prevent overfitting. This is repeating the same in the next two convolutional layers and max-pooling layers with the same pooling size, but different filter sizes for the 2-dimensional convolutional layers. In the last convolutional layer, again we increase the size of the filter to 128 to capture the abundant patterns from the sample image. Now it's time to flatten the image from a 2-dimensional feature map into a 1-dimensional vector. This single-column flatten layer is fed as an input to a fully connected layer. For instance, dropout is applied with a drop probability of 0.5 which can help in removing 50% of the nodes from the neural network. The purpose of implementing the dropout function is that it can only assumes the rate at which the data will truncate. The connection between the neurons is also called the weights. These weight parameters are trainable parameters that the neural network needs to be learned. Even though, fully connected layers are responsible for not only classifying the image into benign or malignant but also learning the features associated with the particular category. Fully connected layers are very essential part of the convolutional neural network architecture[20-30]. The softmax function is used for the output layer; it calculates the probability for each class to which input layer belongs. Therefore, each unit can have a probability of the output class. The softmax activation function is commonly used in various deep learning algorithms in many recommended systems.

$$f(\vec{a})_i = \frac{e^{a_i}}{\sum_{j=1}^{k} e^{a_j}} \qquad (4)$$

From the above formula, 'a' is the input vector to the resulting output layer and 'i' indicates the output unit from 1 to k.

Finally, the validation is done by evaluating the data in the model during training. Once the training is done, it is tested and the accuracy is reported after each epoch. Each epoch returns the validation and shows the ground truth for the validation data and what exactly we are getting. It also reports error tracking matrices. It monitors validation error and tunes hyper parameters to optimize the model for better performance. The Adam optimizer is used which can merge the idea of momentum and learning rate decay to minimize squared error by actually placing the line equidistance from the data points. The Adam optimizer is a powerful technique which takes the idea of momentum from NAG and learning decay from Adagrad and RMSprop. Optimizer updates the model in response to the output of the loss function. The mathematical formation of Adaptive moment estimation is calculated below for mean square error.

For momentum,

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla w_t \quad (5)$$

For learning rate decay

$$v_t = \beta_2 v_{t-1} + (1-\beta_2)(\nabla w_t)^2 \quad (6)$$

For Bias correction,

$$\widehat{m_t} = \frac{m_t}{1-{\beta_1}^t} \quad (7)$$

$$\widehat{v_t} = \frac{v_t}{1-{\beta_2}^t} \quad (8)$$

In equation (7) and (8),'t' implies epoch number or we can say that the value of t = 1,2,3........*i*as per epoch value.

These values are added in below formula.

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{v_t + \epsilon}} * m_t \quad (9)$$

η is the initial learning rate where m_t is the momentum.

4.Performance Evaluation

Making the least amount of mistake should not always be our goal. Different mistakes can have different effects on the model. Usually, a Machine learning model can make several mistakes and it is crucial to decide what kind of mistakes we can live with to choose a suitable machine learning model. It is important to analyse various measures to make informed decision based on its prediction. Therefore, there are four measures of relevance, that is, precision, recall, ROC and accuracy, as depicted in Table 2. Precision is a performance metrics that describes how well the model selects positive result so that the model minimizes errors in estimating positive labels. Similarly, Recall is another evaluation performance metrics that describes how well the model was recalled with the goal of detecting the number of positive labels. Accuracy is another good assessment of model quality for comparison.

Table 2. Performance evaluated between Decision Tree, ANN, SVM and CNN.

Classifier	Decision Tree	ANN	SVM	CNN
Precision	0.85	0.88	0.86	0.95
Recall	0.84	0.87	0.87	0.91
ROC	0.82	0.88	0.86	0.97
Accuracy	83.6%	83.1%	85%	95.35%

We choose CNN machine learning classification model because it is the most accurate machine learning model as compared to SVM, ANN and Decision Tree. We come to the conclusion that CNN is the best and exemplary classification technique indicating the highest accuracy level. The CNN demonstrates excellence in addition to the state-of-the-art models by achieving 95.35% accuracy and estimating precision and recall probability as 0.95 and 0.91 respectively.

Conclusion

A customized binary classificationConvNet model is proposed to classify the multi-texture liver images. The result demonstrated that our model is one of the best model and capable of extracting the features from these images to identify cancer at its early stages. Proper construction of a deep learning model helps prevent the potential problem of overfitting by using various techniques such as dropout and max-pooling activation functions. To address this problem and obtain the required result, 363 CT images of a patient with abnormal liver lesion function are gathered and used for testing and training purposes. With the help of these datasets, our model extracts the lesion areas from the image, analyzes the data and learns from it. The model achieves a classification accuracy of 95.35% with a validation loss of 0.2% using a deep learning-based CNN model.

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