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Research Article

Breast Cancer Detection Using Deep Learning

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ABSTRACT

This research aims to develop an image classification model by integrating long short-term memory (LSTM) with a convolutional neural network (CNN). LSTM, which is a type of neural network, can retain and retrieve long-term dependencies and improves the feature extraction capabilities of CNN when used in a multi-layer setting. The proposed approach outperforms typical CNN classifiers in image classification. The model's high accuracy is due to the data passing through two stages and multiple layers: first the LSTM layer, followed by the CNN layer for accurate classification. Convolutional and recurrent neural networks are combined in the recommended model, which demonstrates exceptional performance on various classification tasks. The model achieved a training accuracy of 0.9899 and testing accuracy of 0.9463 using real data, which indicates its success and applicability compared with other models.

Keywords: Breast Cancer, Deep Learning, CNN, Neural Networks, Hybrid LSTM-CNN.

1. INTRODUCTION

Medical image classification is essential in the field of medicine. It includes a variety of medical image types, including CT, X-ray, MRI, and mammography scans. This classification is based on their distinctive qualities. Convolutional neural networks (CNNs), a type of deep learning, improve the classification process by identifying complex patterns in images. Medical image classification is critical because it affects patient safety, research development, disease diagnosis, treatment alternative selection, and disease progression monitoring [1, 2, 3]. Therefore, with the recent substantial breakthroughs in this field, designing effective models for recognition and classification is imperative. Machine learning is one of the most commonly used fields of artificial intelligence [4, 5, 6, 7]. An individual's ability to learn on their own is dependent on their past experiences [8]. Deep learning is a state-of-the-art innovation in this field that researchers have just discovered [9]. Unlike machine learning, which depends on simpler designs, deep learning attempts to mimic the anatomical complexity of the human brain. Data are represented by these complex structures following a sequence of transformations. To improve accuracy, the input is processed by several layers of a simulated neural network [10, 11]. A hybrid deep neural network combining long short-term memory (LSTM) and CNN is built. The proposed deep convolutional neural network model is applied after a comprehensive examination of the actual breast cancer dataset. To evaluate the effectiveness of the proposed model, we compared it with a number of state-of-the-art classifiers. The contribution of this work lies in the use of real patient data from the oncology center in Wasit Governorate, and the latest model exhibits enhanced accuracy compared with previous models.

2. RELATED WORK

Image classification has gained much attention among researchers owing to its substantial effect on computer vision. Autonomous vehicles, scene detection, and computer-assisted diagnostics are among the various automation tasks that utilize it [12, 13]. Image classification has numerous applications, leading to the development of various techniques aimed at enhancing its accuracy. Most of these strategies depend on deep learning models because of their superior architecture. They achieve consistent results in many image classification tasks, including face identification, object recognition, texture recognition, and medical image classification [14]. Gill and Khehra (2021) showed that deep designs outperform shallow ones, leading to the former's increasing popularity in this domain [15]. Feng et al. (2019) designed a 3D-CNN framework for extracting profound feature representations from MRI and PET scans. FSBi-LSTM was subsequently employed to utilize the hidden spatial data collected from deep feature maps to improve its performance. The effectiveness of the approach was checked using the ADNI dataset. Using this method, the average accuracies obtained for identifying AD from normal control (NC), pMCI from NC, and sMCI from NC are 86.36%, and 65.35% respectively [16]. Mohan et al. (2020) used a specialized tool (LSTM-CNN) to diagnose and classify thyroid illnesses. They utilized the VGG-19 model to assess the affected region and accurately identify and classify the ailment. Compared with older methods like AlexNet-LSTM, ResNet-LSTM, and Vgg16-LSTM, this method is more accurate and efficient because it combines bias field correction with hybrid optimization techniques [17]. Lv et al. (2020) proposed the utilization of a multi-task group bidirectional LSTM model to accurately detect various cardiovascular diseases (CVDs) by analyzing multi-lead ECG signals. The model uses GBi-LSTM and residual group CNNs to extract two distinct sets of features from the ECG data: one representing spatial characteristics and the other temporal characteristics. The model achieves an accuracy of 88.86%, precision of 90.67%, recall of 94.19%, and F1 score of 92.39% [18]. Nagda and Poovammal (2019) proposed a novel method for image classification that combines CNN with LSTM. This method has undergone testing on standard datasets and been compared with other classifiers. The results of these tests showed that the method is dependable and valuable for a range of applications [19]. Areej Rebat Abed and Karim Hussein (2022) developed a diagnostic system using a CNN and linear discriminant analysis to extract representative patterns from data. The classifier was train to differentiate incoming tumors. The experimental results showed an overall classification accuracy of 79%, with 77% precision and 77% recall [26]. Consequently, prior research predominantly depends on the methodologies and precision metrics outlined in each individual study. The present study utilized a hybrid approach known as LSTM-CNN, which achieved notably higher accuracy when compared with earlier investigations. Unlike the proposed model, previous studies used standard data rather than real patient data, which may have contributed to their lower accuracy. The experience and outcomes are further detailed in the Experiment and Results section.

3. PROPOSED MODEL

The proposed model for image classification consists of two layers of deep neural networks: CNN and LSTM. LSTM and CNN are explained comprehensively in the following subsections. The technique uses Python 3.8.1 and TensorFlow 2.2.0 on a 64-bit Windows 11 Pro operating system. The hardware setup includes an Intel Core i7-1255U CPU with 12 cores operating at a base frequency of 2.6GHz and 8GB of RAM.

3.1 LSTM

Recurrent neural network (RNN) architectures, such as LSTM, retain information over extended periods, making them ideal for sequence prediction tasks such as time series forecasting, natural language processing (NLP), and speech recognition. The problem of vanishing gradients can occur while training regular RNNs on long sequences; LSTMs resolve this issue through their rating system, which instructs them to retain specific information while forgetting others. As shown in Fig. 1., the main components of an LSTM are as follows:

- Cell State: This state serves as the storage for the network's assets throughout the long term. At the gate level, information can be added to or subtracted from the cell state.
- Hidden State: The LSTM unit outputs this at each time step to predict or pass information to the next time step.
- Input Gate: Cell status information is added through this gate. Each cell state component receives a value between (zero and one) from the input and previous concealed state.
- Forget Gate: This gate regulates the retention of the previous cell state. The function accepts the input and the previous hidden state as inputs and outputs a value that ranges from (zero to one) for each component of the cell state.
- Output Gate: This gate provides cell state information for the hidden state. The input and prior concealed state are used to return a (zero to one) value for each cell state component.

LSTM is used in machine translation, speech recognition, and sentiment analysis because they long-range dependencies in sequential data [20, 21].

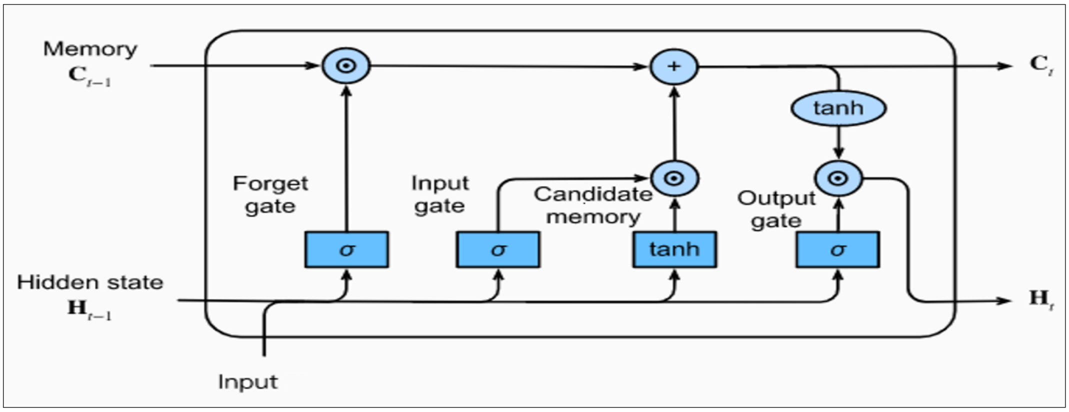

Fig. 1. *LSTM*

3.2 CNN

Biological neural networks [22, 23, 24] influence CNNs, a type of multilayer perceptron neural network. The fully connected layer architecture implies a link between each neuron in one layer and every neuron in the layer behind it. CNNs require less preprocessing compared with traditional image classification methods. A CNN consists of an input layer, an output layer, and many hidden layers [25]. The hidden layers are made up of several convolutional layers that perform convolutions among themselves and multiplication or dot-product operations. Fig. 2 illustrates the basic structure of a CNN.

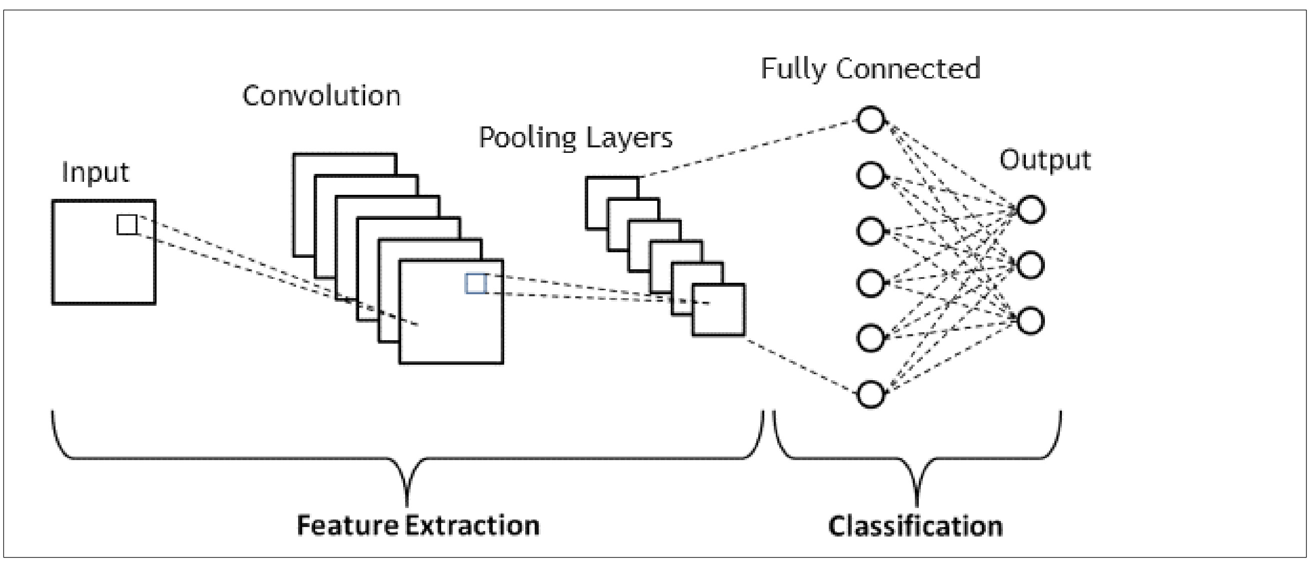

Fig. 2. *Basic Design of CNN*

Local spatial coherence helps CNNs extract important characteristics from images and classify them well. CNNs can extract important data, making them ideal for specific tasks.

3.3 LSTM-CNN

The proposed LSTM-CNN model architecture is shown in Figure 3. Images start at the input layer. The batch normalization layer receives this input layer. The batch normalization layer transforms the activation function in the previous layer to maintain a normal distribution with a mean activation near zero and a standard deviation near one. Although all features are normalized, each input feature map has its own normalization. The normalization axis is specified by an axis option. We normalized the data during training by applying statistics to batches and using moving averages, as shown in Fig. 3.

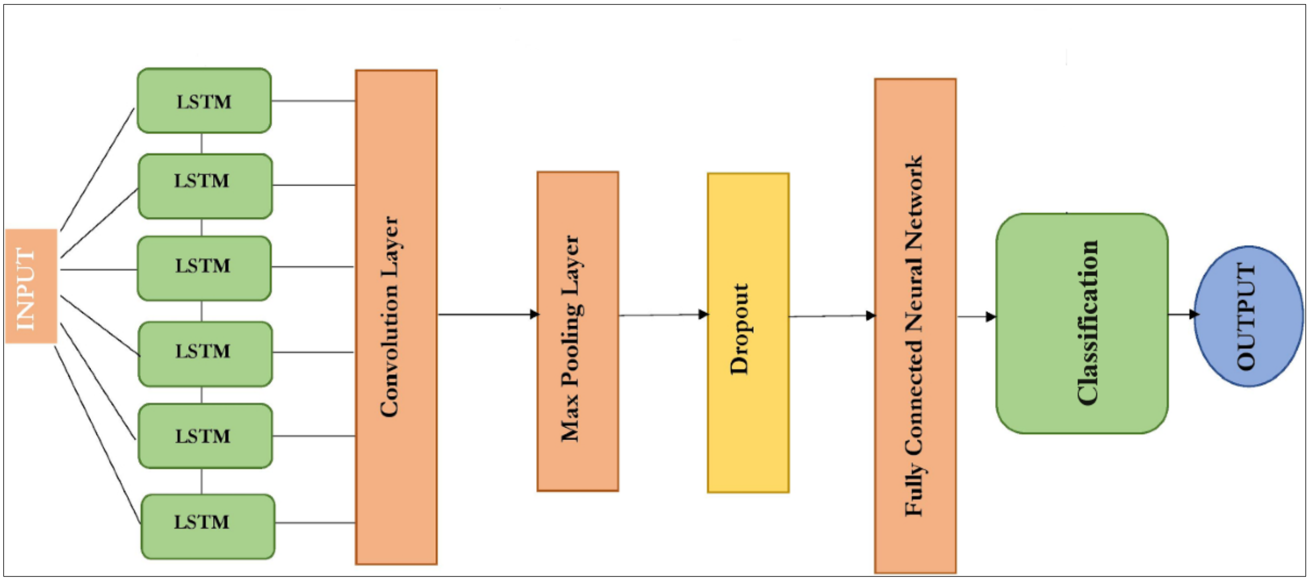

Fig. 3. *LSTM-CNN Neural Network Architecture*

The hybrid model of LSTM-CNN incorporates the input from the LSTM into the CNN, enabling the CNN to leverage its feature extraction skills and the sequential modeling of the LSTM. This procedure transfers the sequential dependencies from the LSTM layers to the CNN. The CNN then extracts hierarchical features, making this model well-suited for these tasks. Implementing this model necessitates comprehensive expertise and a wide-ranging understanding of the situation. The user's text is [21].

The hybrid model has numerous advantages and achieves exceptional performance by capturing spatial properties and intricate patterns found in sequential data.

4. METHODOLOGY

The proposed method for breast cancer detection involves a series of steps. The initial step involves acquiring a mammogram image, followed by pre-processing operations. These operations include converting the images to color, resizing them, and then normalizing them. The data are then partitioned into a training set and a test set, which are then fed into the hybrid model to classify the image and identify the presence of infection. After receiving the data from the source, They undergo pre-processing before being partitioned. We partition the dataset into 70% training data and 30% testing data and then implement the LSTM algorithm. The CNN model inputs the flattening process output from the LSTM model and ultimately reaches the classification stage. The feature extraction process goes through several stages:

- Input Layer (The original images were grayscale images and were converted to color images to increase the clarity of the affected tissues.)
- Convolutional Layer (3 × 3 filters were applied and the ReLU activation function.)
- Pooling layer (2 × 2 max pooling was used to reduce the feature maps.).
- Flattening (Feature maps were converted to a single vector.)
- Fully Connected Layer
- Output Layer

5. DATASET

The data were acquired from the oncology center in Wasit Governorate, Iraq. One of the biggest limitations in this work is the process of obtaining real patient data because it requires formal approvals. The data used are MRI radiographs of patients in this center, and the images ($N = 5993$) are divided. The training data consist of 2067 instances labeled as benign and 3522 instances labeled as malignant. The testing data consist of 216 instances classified as benign and 188 instances classified as malignant. The data are grayscale and vary in size.

5.1 Converting Images to Color Images

Converting mammography scans into a color gradient might be advantageous for visualizing and understanding images. A commonly used technique involves linking grayscale data with a color scale, such as a heat map, where cooler shades represent lower intensities and warmer shades represent higher intensities.

5.2 Resizing Images

After applying the RGB approach to the modified images, the next step involves adjusting the image size. To employ feature extraction techniques, all digital mammography images must have identical dimensions. Digital mammography images are of high quality, so the image size can be reduced without introducing any distortion. The mammography images are resized to dimensions of 150×150 pixels.

5.3 Normalizing Images

Normalization is the conversion of values to fit within a specific range. This procedure frequently involves manipulating the numbers to achieve an average of zero and a standard deviation of one. Normalization is crucial in training machine learning models because it enhances the stability and efficiency of the optimization process. In addition, ensuring uniform formatting of the input data improves the model's ability to generalize.

5.4 LSTM-CNN model

The LSTM model operates by sequentially transferring data from the beginning to the end. The images underwent 10 stages before reaching the flattening layer without any processing by the classifying layer. We use the results from this stage as input for (CNN), which will handle the classification process. The CNN design uses the LSTM model's output as its input. The CNN employs the modified linear unit (ReLU) activation function and consists of four Conv2D layers. After each layer, we add a maximum pooling layer with a filter size of 3x3. The SoftMax function activates two dense layers that follow the flat layer. The training parameters include a batch size of 32 and 25 epochs and the Adamax optimizer.

6. EXPERIMENT AND RESULTS

This model has six convolutional layers with a filter size of 3×3. The ReLU is a mathematical function. The purpose of this layer is to apply convolution to the output of the previous layer using a set of filters that may be adjusted through learning. The convolutional operation is determined by the weights assigned to these filters. We apply all filters across the entire height and breadth of the input volume to generate 2D activation maps for the relevant filters. The filter has a comparable input depth. We can also address this issue using three parameters. Zero-padding is the act of appending zeros to the edges of the input to prevent it from becoming overly large.

Training the deep learning model with a large quantity of images can enhance its accuracy and reduce loss. Our proposed model was built on an authentic dataset from the oncology center in Wasit Governorate. The training process utilized a hybrid model known as LSTM-CNN. We trained the model using 25 epochs and a batch size of 32. The total training duration was 2400 seconds. Adding more data to the training dataset and extending the training duration can improve the model's precision. If the training loss exceeds the validation loss, then the model is insufficient. If the training loss is less than the validation loss, then the model is overfitted. Conversely, the goal is to achieve balance between the training and validation losses.

The subsequent diagrams (Figs. 4 and 5) illustrate the values of the trained model, notably its loss and precision. The relationship between the trials and epochs is depicted by the orange curve. The blue curve represents the training epochs and the model obtained via the confusion matrix. The accuracy rate increases in direct proportion to the number of collected datasets.

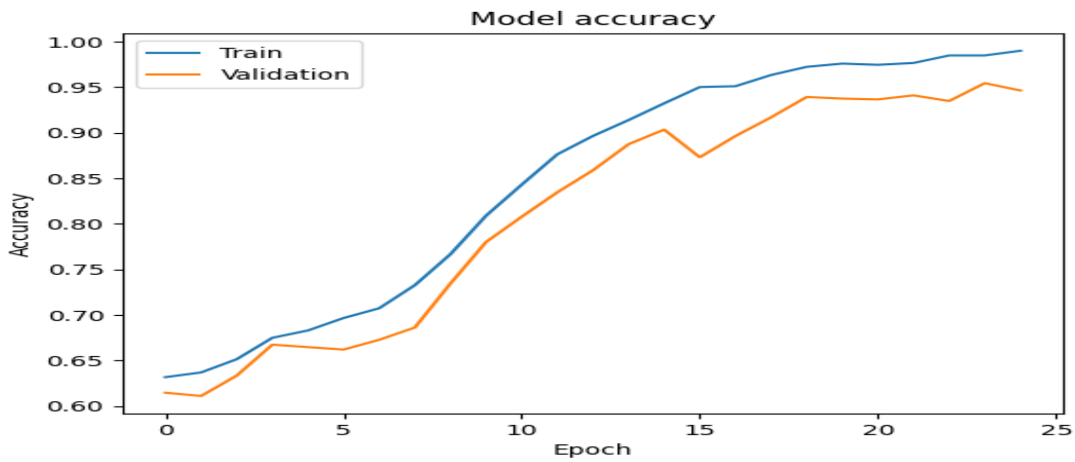

Fig. 4. *Accuracy Value*

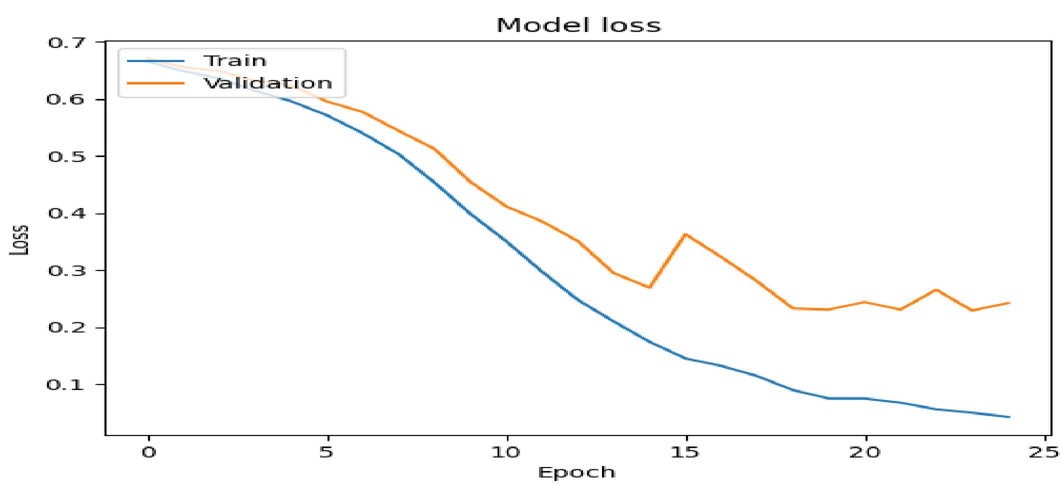

Fig. 5. *Loss Value*

This is in addition to the findings from a random test, as shown in Fig. 6.

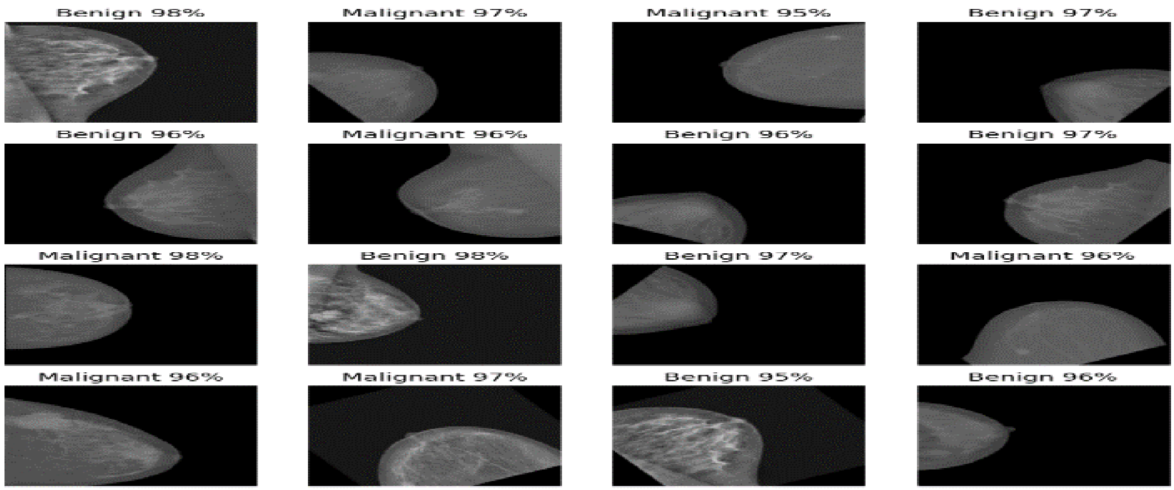

Fig. 6. *Results of a Random Test*

The accuracy, precision, recall, and F1 score are displayed in Table 1 based on the results provided in Fig. 6.

TABLE I. THE ACCURACY, PRECISION, AND OTHERS

Type	**Accuracy**
Accuracy of training	0. 9899
Accuracy of testing	0. 9463
Precision	0. 9409
Recall	0. 9737
F1 Score	0. 9570
Mean Squared Error	0.05
RMSE	0. 2316

Fig. 7 shows the actual results and simulations.

	precision	recall	f1-score	support
0	0.96	0.90	0.93	431
1	0.94	0.97	0.96	687
accuracy			0.95	1118
macro avg	0.95	0.94	0.94	1118
weighted avg	0.95	0.95	0.95	1118

Fig. 7. *Results of a Random Test*

Table 2 compares the current research with previous work, highlighting the type of data used, the method employed, and the accuracy results.

TABLE II. THE COMPARISON WITH RELATED WORK

No.	Author (Year)	Dataset (Images)	Method	Accuracy
1	Lv et al. (2020) [54]	Database (CCDD)	MTGBi LSTM	88.86%
2	Areej Rebat Abed and Karim Hussein (2022)	DDSM dataset and 1208 images	CNN	79%,
3	Feng et al. (2019)	ADNI dataset	FSBi-LSTM	86.36%, and 65.35% respectively
4	Mohan et al. (2020)	DDTI dataset image of ultrasound	LSTM-CNN	89.4
5	Nagda and Poovammal (2019)	IDC dataset	LSTM + CNN	84.548
6	Current research	Real dataset	LSTM-CNN	94.63

7. RECOMMENDATIONS

1. Creating a mobile application for the proposed system is recommended so that doctors can use their mobile devices to access the diagnosis.
2. A different collection of data can be utilized.
3. Data mining techniques can be employed to predict how a disease will progress over a specified period.

8. CONCLUSION

This study aims to enhance the accuracy of image classification by adopting a hybrid model that combines LSTM and CNN. Our suggested model has demonstrated performed better than other contemporary classifiers, such as CNN and LSTM. To determine the level of significance of our model, we conducted a test using real data obtained from a cancer facility. The breast cancer dataset was obtained using the following metrics: an F1 score of 0.9570, a recall of 0.9737, a training accuracy of 0.9899%, and a test accuracy of 0.9463%. The model established the foundation for future advancements by utilizing its several layers, effectively addressing overfitting in the presence of potent GPUs, and improving dropout layers, all while attaining a significant level of accuracy through multiple LSTM-CNN layers.

To the best of our knowledge, this issue has been studied. Nevertheless, the accuracy of the classification results was inadequate. The primary objective of our study is to address deficiencies in accuracy and data, thereby contributing to a superior degree of precision and ultimately enabling in a highly accurate diagnosis. This study utilized authentic patient data gathered from the Wasit Governorate Oncology Center. The application of real data assists in identifying authentic injuries, hence facilitating the training process on a realistic model.

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