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An Image Classification and Retrieval Hybrid Model for Larger Healthcare Datasets using Deep Learning

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Abstract

Objectives: The objective of this work is to obtain an efficient medical image retrieval and classification from a larger healthcare datasets using Novel approach. **Methods:** In this study five different classes of Medical images are taken for input, features are extracted using GLCM (Grey Level Co-occurrence Matrix) by image attributes such as dissimilarity, correlation, homogeneity, contrast, ASM, and energy. The photos are examined at several angles (0, 45, 90, and 135) to extract the characteristics using the layers. The received feature vectors are input into the most often used deep learning models Artificial Neural Networks (ANN) and Convolution Neural Networks (CNN) for image classification. Then CNN model is integrated with a deep learning model based on Long-Short Term Memory (LSTM), which incorporates additional layers into its structure and works on large datasets. Further the retrieval performance is improved by Euclidean Distance Technique. **Findings:** Performance evaluation is performed by comparing and analyzing the experimental findings of proposed methods, ANN, CNN and CNN-LSTM yields the retrieval accuracy of 97.79%, 98.78% and 99.4%. The Precision, Recall and F1-Score are also compared, and they are more accurate when picture classification is performed on larger healthcare datasets. **Novelty:** The additional feature extraction using GLCM and the proposed hybrid model can extract better medical image features, and achieve higher classification accuracy compared with earlier image classification models.

Keywords: ContentBased Image Retrieval; Grey Level Cooccurrence Matrix; Artificial Neural Networks; Convolution Neural Networks; LongShort Term Memory; Cloud Computing

1 Introduction

In recent times, medical imaging plays an important role in timely treatment, diagnosis, and detection of several diseases like Alzheimer, Brain Tumor, Breast Cancer, Covid, Tuberculosis etc[1]. With the rapid advancement in medical imaging and automatic diagnosis systems, plenty of medical images are being collected, stored in DICOM (Digital Imaging and Communications in Medicine) format. Many medical imaging devices such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and X-ray are used to acquire medical images, extremely important for diagnosis, detection, monitoring and treatment planning[2]. Deep learning-based approaches for content-based image retrieval (CBIR) of medical images are a dynamic field of research, but suffer from some significant limitations. First, they are heavily reliant on labeled data, which can be challenging and costly to acquire. Second, they lack transparency and explainability, which limits the dependability of deep CBIR systems[3,4]. The quality of picture searches by using a strategy that uses multiple deep neural networks and K-Nearest Neighbor algorithms in content-based image retrieval[5]. Recurrent Neural Networks (RNN) are used to automatically generate sentences, whereas Convolutional Neural Networks (CNN) are used to extract the properties of images[6]. Due to the widespread use of cloud storage large image libraries are easily accessible, Text-based searches are common and simple, image-based searches are more sensitive and intelligent[7]. More and more medical images are appearing in experimental diagnosis due to the fast expansion of the medical profession and the ongoing development of medical technology. The study of medical images is easy now to identify these images properly and accurately[8]. Due to variation in the shape and size of the images, the retrieval task becomes more monotonous in the large medical databases[9]. A difficult task for people needed in various sectors, especially the healthcare industry is the accuracy and latency of the CBIR technology on cloud storage servers.

A precise diagnosis is important for the handling of any disease in its early stage. Content-Based Medical Image Retrieval (CBMIR) is used to find similar medical images in a huge database to help radiologists in diagnosis. The main difficulty in CBMIR is semantic gaps between the lower-level visual details, captured by computer-aided tools and higher-level semantic details captured by humans[10]. Even for the Internet of Things (IoT) communication between smart devices requires significant data processing since it deals with enormous amounts of data in the form of photos or videos. For a variety of Internet of Things applications, the image retrieval system decreases the computational overhead[11]. For those needed in various industries, especially the healthcare industry, the accuracy and latency of the CBIR approach on cloud storage servers is a difficult task[12]. Medical images are used for more than simply diagnosis; they are also used to help people comprehend various diseases causes and treatments. There is an urgent need for effective and accurate content-based medical image retrieval (CBMIR) method to accomplish all of these goals[13]. Model for predicting COVID-19 severity from CT scans and clinical data[14]. A dataset of 1,800 MRI images from two types of diagnoses- glioma tumor and pituitary tumor, is used to test the suggested models[15]. Employing two VGG network models (VGG16 and VGG19) and a deep CNN method, a hybrid deep learning strategy was used to detect and classify Diabetic Retinopathy (DR)[16]. The Hybrid Deep Learning (HDL) models have demonstrated consistent and improved performance by combining the best features of two or more solo DL or DL with Machine Learning (ML) models. Research shows that HDL is actively used in both medicinal and non-medical purposes[17].

A variety of sets of images and datasets in existing techniques perform medical image retrieval such as, Computed tomography (CT)[1], Chest CT images of COVID[2], CE-MRI and OASIS dataset[8], CE-MRI[10], Diagnosis of Liver Tumour[18], CRC-5000, CE-MRI, Diabetic Retinopathy (DR)[16], NCT-CRC-HE-100 K[19], X-ray images and Computerized Tomography (CT) scans, including pneumonia, tuberculosis, and lung cancer[20] etc., are used in the current approaches to perform medical image retrieval. The following are the primary contributions of this study extracting additional features in terms of parameters such as distance, angle, resolution, level, and symmetric values. These values are retrieved from the pictures using the GLCM technique by image attributes such as dissimilarity, correlation, homogeneity, contrast, ASM, and energy, which helps in improving image classification. We first analyzed with ANN and CNN Deep Learning models then merged CNN and LSTM models to create a hybrid model and applied it to healthcare datasets. Because of the number of layers contained in this new approach model, the accuracy % has improved elastically when large datasets are acquired; further the retrieval performance is improved by Euclidean Distance Technique.

2 Literature Survey

Selvaraj, S., et al. (2023)[1] offered Very Deep Convolution Networks for Large-Scale Image Recognition from the Visual Geometry Group Lab by developing VGG-16 trained imageNet weights in 528 MB for saving disc space in memory and increasing network bandwidth. Several layers are employed in this VGG 16 architecture to separate the picture classification function and get the precise images from the repository with more precision.

A. B. Godbin et al. (2023)[2] suggested a Random Forest and GLCM hybrid model employing CT images of COVID-19 patients. To extract the original pictures from the sources, Support Vector Machines, K-nearest neighbors, Random Forest, and XGBoost classifiers are utilised to perform quick diagnostics from the image repository. It provides the healthcare sector with increased precision and capacity for producing medical records effectively.

Hung, B. T et al. (2023)[5] proposed a method known as Average Precision (AP) and Mean Average Precision (mAP) measures to find the similarity measure of the distance between the feature vectors and conducted model experiments with the Oxford-IIIT Pet Image Dataset and a Kaggle competition self-collected dataset. Accuracy, confusion matrix, and F1 scores are compared with prior models; average precision values are increased with larger deviation.

K Chethan et al. (2023)[8] Local Ternary Pattern (LTP), and Histogram of Oriented Gradients (HOG) are used to extract the features from the medical images. Therefore, an Infinite by incorporating the Feature Selection (Inf-FS) technique, the classification process utilizing the sparse auto encoder based DNN is improved by choosing the best features from the feature vector. Additionally, the Euclidean Distance methodology helps the suggested method's retrieval performance. With enhanced sensitivity, specificity, and error rate, the sparse auto encoder-based DNN classification method achieves an overall accuracy of 95.34% in the OASIS dataset.

Hirald Dwaraka Praveena et al.[9] In this study, new Pap smear dataset is used as the source for the input medical images, and image normalization technique is used to enhance the visible quality of the obtained medical images, by extracting the Color and Texture feature vectors using a Modified Local Binary Pattern (MLBP) and a Histogram of directed Gradients (HOG), the semantic gap between the feature vectors is greatly reduced. Then the obtained feature vectors are fed to the Hybrid feature based Independent Condensed Nearest Neighbor classifier (ICNN) to classify model almost achieved 98.88% of retrieval accuracy. The model uses small number of image databases is one of its limitations.

NV Shamna et al.[10] introduced the Histogram of Gradient (HoG) with Local Ternary Pattern (LTP) feature extraction method is suggested for automatically retrieving medical pictures from the Contrast-Enhanced Magnetic Resonance Imaging (CE-MRI) database. In comparison to the current Random Forest (RF), the proposed HoG-LTP approach achieves greater accuracy. This study limits optimal feature extraction in medical imaging to remove redundant information from the datasets of images.

Rajesh Kumar et al.[11] Authors implemented the Geometric Invariant Point Bilateral Transformation (GIPBT) algorithm's proposed feature extraction technique offers texture information and proposed similarity measure method is Discriminant Kernalized Disparity (DKD) metric, Different medical database images are used to simulate and test the system's retrieval performance in terms of Retrieval Efficiency, Normalized Average Rank of Retrieval, Precision, Recall, SSIM, and processing Time.

Heng Zhang et al.[18] in this work, CT images of patients with liver tumors were feature segmented using CNN. It proved to be precise and effective in segmenting images. A scientific rationale for the segmentation of liver tumor in CT images was provided by the algorithm's high resolution.

Huiyi Hu et al.[21] In this study, a Content-Based Gastric Image Retrieval (CBGIR) approach is put forth that creates binary hash codes using a modified ResNet-18 to facilitate quick and precise picture retrieval. A Gastric precancerous diseases GPD data set was used to evaluate the suggested method, which outperformed other state-of-the-art conventional methods with a classification accuracy of $96.21\pm$ 0.66% and a mean average precision of 0.927 ± 0.006.

Metwally Rashad et al.[13] in this paper proposed an effective approach (RbQE) for the retrieval of computed tomography (CT) and magnetic resonance (MR) images, RbQE is based on extending the features of querying and exploiting the pre-trained learning models AlexNet and VGG-19 to extract compact, deep, and high-level features from medical images.

Saeed Mohsen et al.[15] in this study, authors proposed two classification models ResNext101_328d and VGG19, for pituitary and glioma, two forms of brain tumors to a dataset of 1,800 MRI pictures divided into two groups of diagnoses- glioma tumor and pituitary tumor, for each image. For the benefit of both patients and clinicians, the ResNext101_32 8d and VGG19 models can be used to MRI medical pictures to hasten diagnosis.

Brahami Menaouer[16], in this paper authors implemented a hybrid deep learning strategy to Diabetic Retinopathy (DR) detection and classification according to the visual risk associated with the severity of retinal ischemia utilizing deep CNN method and two VGG network models (VGG16 and VGG19). An ensemble of online datasets including 5584 photos were used in the experiment, and the results showed accuracy of 90.60%, recall of 95%, and F1 score of 94%. The study's usage of a small number of photos from current databases is one of its limitations. The datasets' quality and balance, which are used to create a DR screening system, are crucial in this regard.

Masoud Khazaee Fadafen et al.[19] authors proposed method to classify numerous tissues in Histopathology images (His), the dilated ResNet (dResNet) structure and attention module are employed to create deep feature maps. After the features have been chosen, data is input into a deep Support Vector Machine (SVM) based on an ensemble learning technique called DeepSVM. To validate and evaluate the hybrid technique, data from the CRC-5000 and NCT-CRC-HE-100 K datasets were studied.

Jasmine P P et al.[20] The goal of the suggested framework study is to identify and categorize different lung diseases, such as pneumonia, tuberculosis, and lung cancer, using volume datasets and standard X-ray and Computerized Tomography (CT) scan pictures. Deep learning techniques are exciting and effective fields that expand the machine learning field where CNNs are trained to extract characteristics and offer enormous promise from datasets of images in biomedical applications. This study limits the optimizer, learning rate and further required improvements in the classification accuracy of the proposed CNN models.

3 Proposed Method

In the proposed method, efficient image retrieval over the medical images is performed using additional feature extraction, Classification models and Euclidean distance techniques are used. The following are the stages that this medical picture retrieval system takes. Figure 1 shows the workflow model of the proposed method.

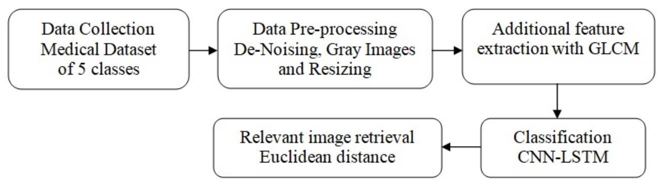

Fig 1. Workflow model of Proposed System

3.1 Data Collection

In this hybrid model technique, various sizes of data sets were acquired from online sources and used in tests, with the quantity of input photographs varying in each dataset. A minimum of 4MB and a maximum of 95MB of 5 Classes of different diseases photographs are used as input for this experiment. Table 1 depicts the total number of data sets as well as the number of photos in each dataset and picture categorization classes. Figure 2 shows the sample images of medical dataset.

Table 1. Medical image dataset

Class#	Target Class	Data Size (MB)	Input image (4525)
1	Alzheimer	4.89	937
2	Brain Tumor	19.8	993
3	Breast Cancer	29.5	952
4	Covid-19	82	945
5	Tuberculosis	95	701

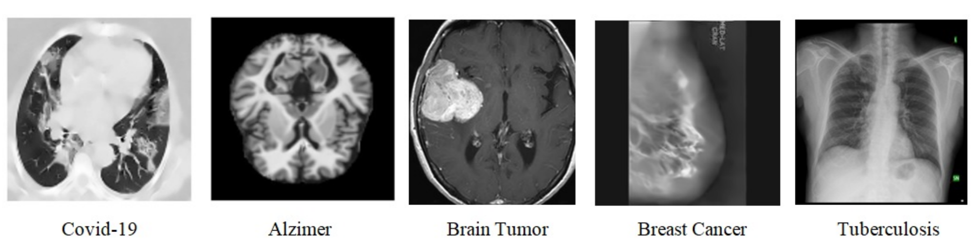

Fig 2. Sample medical images

3.2 Data Pre-processing

One of the most crucial stages of the image pre-processing is De-noising. De-noising of an image refers to the process of reconstruction of a signal from noisy images, the unwanted noise removed by using fastNlMeansDenoisingColoredimage (imp, none, 8, 6, 7, 15) method to analyze it in better form. Then image is converted into greyscale using cvtColor(img, cv2.COLOR_BGR2GRAY) and images resizing done with resize(gray, (128,128)) method.

3.3 Additional Feature Extraction

After image pre-processing feature extraction achieved using GLCM global descriptor, GLCM retrieved additional information from its layers to find the precise photos from the repository, their characteristics in terms of parameters such as distance, angle, resolution, level, and symmetric values. These values are retrieved from the pictures using the GLCM technique by image attributes such as Dissimilarity, Correlation, Homogeneity, Contrast, ASM, and Energy [1–3]. The photos are examined at several angles (0, 45, 90, and 135) to extract the characteristics using the layers. Figure 3 depicts the phases in the GLCM method and Figure 4 shows sample images features extracted using GLCM method.

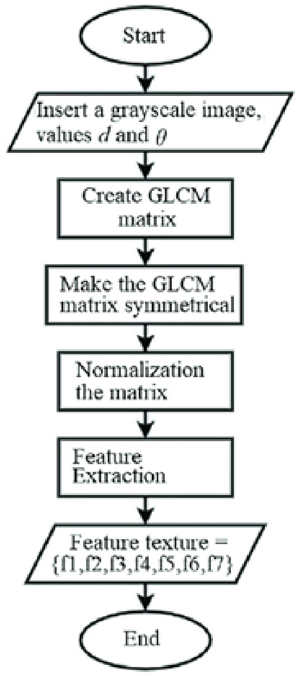

Fig 3. GLCM Steps

	dissimilarity_0	dissimilarity_45	dissimilarity_90	dissimilarity_135	correlation_0	correlation_45	correlation_90	correlation_135	homogeneity_0
0	30.736916	32.575442	27.894182	32.534729	0.781313	0.764076	0.802819	0.762999	0.455008
1	30.456047	33.104969	28.905615	33.728668	0.780352	0.756658	0.793830	0.750082	0.470101
2	32.560849	34.232700	28.665523	34.308273	0.771272	0.761546	0.808518	0.758617	0.463788
3	33.395452	34.849636	31.126651	34.856920	0.766454	0.755944	0.790607	0.756903	0.420613
4	29.613694	29.885276	23.927337	30.223335	0.828779	0.829478	0.878776	0.827218	0.470974

homogeneity_45	...	contrast_135	ASM_0	ASM_45	ASM_90	ASM_135	energy_0	energy_45	energy_90	energy_135
0.435718	...	3231.741415	0.174483	0.156998	0.171913	0.157505	0.417712	0.396229	0.414625	0.396869
0.451465	...	3585.774454	0.172437	0.155972	0.171425	0.155325	0.415256	0.394933	0.414035	0.394113
0.444993	...	3662.425468	0.178560	0.162075	0.177712	0.162131	0.422563	0.402585	0.421559	0.402655
0.400133	...	3345.376431	0.157093	0.141099	0.158260	0.140762	0.396349	0.375632	0.397819	0.375183
0.456010	...	2937.668314	0.183045	0.166926	0.182494	0.167607	0.427838	0.408566	0.427193	0.409398

Fig 4. Features extracted using GLCM Method

3.4 Classification Models

In order to categorize the samples of the five classes mentioned during the data collection phase, the extracted feature vectors are fed into three different classification techniques. After the samples of the five classes have been classified, the relevant cell images are retrieved by calculating the distance between the extracted feature vectors using the Euclidean distance measure.

3.4.1 Artificial Neural Network (ANN)

ANN is a method used to obtain the most accurate pictures from a numerical data collection. The GLCM correlated confusion matrix numerical value must be fed into the ANN to build trained datasets. An ANN consists of interconnected processing units called artificial neurons or nodes. These nodes are organized into layers, typically including an input layer, one or more hidden layers, and an output layer. The connections between the nodes are represented by weights, which are learned during the training process. After the training set's accuracy has been enhanced, it is used as an input to the validation data set. All of these operations are carried out in the model's hidden layer using multi perceptron layers. A Confusion matrix was generated using the picture parameters, and it was trained to have a less initial accuracy. Artificial Neural Network is utilized to offer more layers in the hidden section of the multi layers for enhancing the accuracy of the retrieved picture with its attributes. The accuracy level has increased, but the bandwidth and latency are somewhat different and not up to the intended level.

3.4.2 Convolutional Neural Network (CNN)

The CNN model, often known as the Harts model, is one of the most widely used image retrieval models in CBMIR. Include the samples in the reduced set first, and then validate each sample by comparing it to its closest neighbor in the compressed set. If the label fits the smaller set, the relevant cell images are identified; otherwise, further image samples are added during condensation. Even though the CNN model iterates until all training picture samples are accurately classified, retaining the sample captioning reduces computational overhead and system storage, which is one of the CNN model's key advantages. A Confusion matrix was generated using model and trained to have less initial Accuracy. Then, Convolutional Neural Networks is added more layers to increase the accuracy.

3.4.3 Proposed Hybrid Model CNN-LSTM

Because the GLCM technique feature extraction dataset is totally numerical, the suggested hybrid model of this research combines CNN and LSTM models with a binary mode. When these two models are merged, more layers actively contribute to obtaining accurate pictures, and the values generated when building the confusion matrix are more accurate than in the prior models. Though photos are analyzed from various perspectives in the GLCM technique, the combined approach analyses the images more accurately to anticipate the exact match of the characteristics in order to eliminate dissimilarity. Because of the additional layers in this hybrid model, the accuracy threshold is increased.

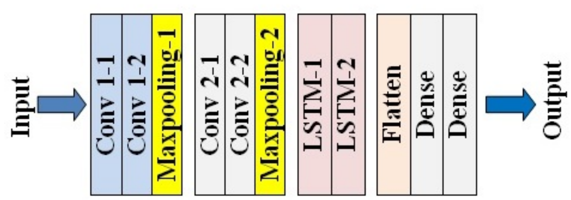

Fig 5. CNN-LSTM Layers Architecture

The various layers used for the proposed model is shown inFigure 5. CNN-LSTM stands for Convolutional neural networks and Long Short-Term Memory, architecture that incorporates convolutional operations. CNN-LSTM combines the ability of LSTMs to capture long-term dependencies with the ability of convolutional neural networks (CNNs) to extract spatial features from data. In a standard LSTM, the input is treated as a sequence, and the recurrent connections allow the network to capture dependencies between elements in the sequence. However, LSTMs do not explicitly consider the spatial structure of the data. CNN-LSTM addresses this limitation by incorporating convolutional operations into the LSTM framework.

3.4.3.1 **Representation of the Confusion Matrix**. A machine learning system can forecast using the Confusion Matrix. A 2*2 matrix with computed and actual classes as rows and columns is constructed for validation. Four alternatives are considered as values.

- True Positive (TP)
- False Positive (FP)
- False Negative (FN)

• True Negative (TN)

The predicted value is TP when the projected value matches the actual value and the actual value is positive. The model predicted a negative outcome, and the actual value is negative. FP is an abbreviation for false projected value, which is negative but was predicted to be positive by the model. It is also referred to as a kind 1 error. FN is a negative value that is anticipated to be false and is referred to as a type 2 error.

3.4.3.2 **Calculation of Cross-Validation**. As an example, it is a mathematical approach used to classify the efficacy of learning from the repository's inputs. A single instance is split into numerous examples that go through countless iteration to achieve an accurate result. The same approach is utilized in both calculated and actual class members each time, and the results are used for analytics and decision-making. Equation (1) computes the accuracy of each iteration with respect to the instances, where all of the values are taken from distinct examples.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

Root Mean Square Error (RMSE) may be determined using the average values of all cases evaluated in the iterations. The followingEquation (2) is used to determine the value.

$$RMSE = \frac{\sqrt{FP+FN}}{\sqrt{TP+TN}} * \frac{1}{\sqrt{FP+FN}} \tag{2}$$

The classifier's accuracy is determined by the positive false rate and the positive true rate. The equations 3, 4 are used to express it.

$$Positive\ True\ = \frac{TP}{TP+FN} \tag{3}$$

$$Positive\ False\ Rate\ = \frac{FP}{FP+TN} \tag{4}$$

3.5 Medical Image Retrieval based on Euclidean Distance

The Euclidean distance measuring approach for image retrieval determines how similar the two images are i.e., input image and retrieval image. Due to its usefulness and efficiency, this Euclidean distance-based similarity metric is employed. The distance between the two picture vectors is determined as the square root of the total of the squared absolute differences. The following formula expresses the relationship between the query picture and database images:

$\triangle d = \sqrt{\sum_{i=1}^{n} (Q_i - D_i)^2}$

In this proposed model, by employing a suitable feature extraction and classification, an efficient picture retrieval and classification of image types are accomplished. The additional feature extracted from images using GLCM, because it is resilient to large databases, the Hybrid model is used for the categorization is utilized in this medical image retrieval.

4 Experimental Setup and Performance Evaluation

The proposed classification retrieval model applied to the medical dataset of 5 different classes such as Alzheimer, Brain Tumor, Breast Cancer, Covid, and Tuberculosis. The preceding studies, conducted with diverse datasets utilizing the Google Co-Lab platform and the Python language, yielded results that were sufficiently accurate to outperform the prior models. In medical dataset of five classes 80% of images are used for training and 20% of the images are used for the Testing retrieval purpose. The performance metrics used to analyze the models is Accuracy, Precision, Recall and F1-Score. Although CNN and LSTM models are merged, the features derived from images using GLCM play a significant part in this research.

Table 2 shows Precision, Recall and F1-Score for the classes of medical images and models such as ANN, CNN and Hybrid Model. However, the Hybrid model has better performance with additional feature extraction comparatively with ANN and CNN. Based on the data, a confusion matrix was built and compared to CNN and ANN to determine the optimal accuracy levels. When we look at the findings of each epoch, we see that the data consistency level varies depending on the number of layers in the hybrid models. The performance metrics for each classifier is graphically shown in Figure 6.

However, when this hybrid model is used with CNN and the LSTM model, the picture classification accuracy is about 99.4%. The main gain of this method is to reach maximum accuracy by combining classifiers.

Table 2. Classification performance metrics for different classes of images

Image Class	ANN			CNN			CNN-LSTM (Hybrid Model)		
	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Alzheimer	0.97	0.96	0.97	0.98	0.99	0.99	1	0.98	0.99
Brain Tumor	0.96	1	0.98	1	0.96	0.98	0.99	1	1
Breast Cancer	0.99	0.97	0.98	0.99	1	0.99	0.98	1	0.99
Covid-19	0.97	0.96	0.97	0.98	0.98	0.98	1	1	1
Tuberculosis	0.99	0.99	0.99	0.99	1	0.99	1	0.99	0.99
ALL (Avg)	**0.976**	**0.976**	**0.978**	**0.988**	**0.986**	**0.986**	**0.994**	**0.994**	**0.994**

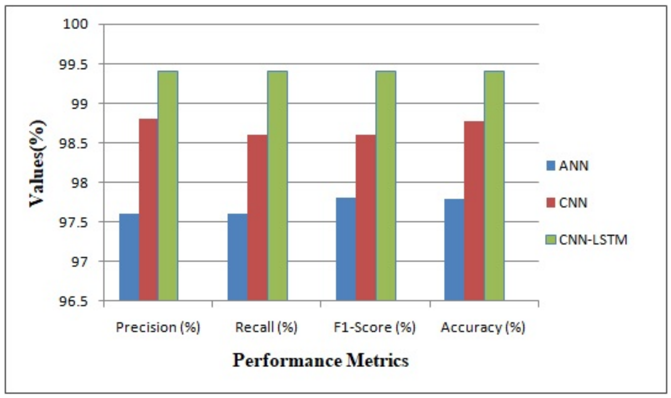

Fig 6. Comparative analysis of performance metric for medical dataset

4.1 Comparison with ANN and CNN Models

The findings are compared to the confusion matrix values and parameters from the preceding tests, such as Accuracy and Loss. Despite the fact that the studies were carried out over repeated epochs, the accuracy levels remained consistent at 95% to 99% throughout all cycles. When the hybrid model is compared to the prior ANN and CNN models, the accuracy can be enhanced with a minimum of 50 epochs owing to the feature extraction function of the hybrid model layer. The Figure 7 depict the accuracy level and its comparison.

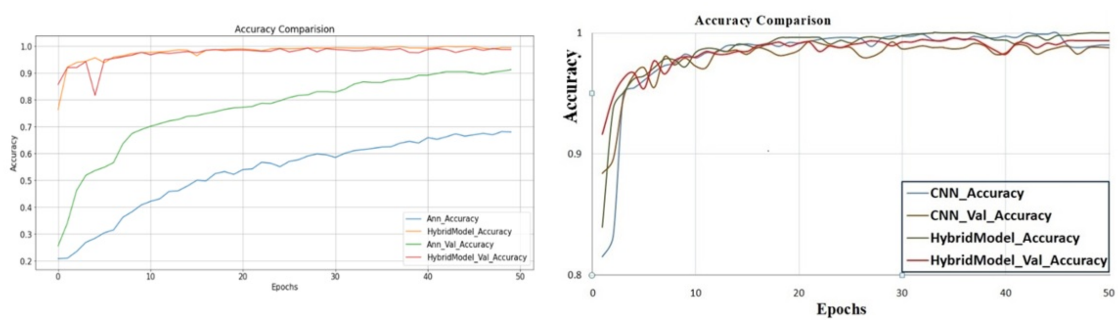

Fig 7. Accuracy Comparison of ANN, CNN with Hybrid Model

The findings are compared to the confusion matrix values and parameters from the previous tests, such as Accuracy and loss. Despite the fact that the studies were carried out using repetitive epochs, their loss levels were lowered at a rate of 10% to 25% at all cycles. The hybrid model is compared to the prior LOSS ANN and CNN model. Because of the hybrid model layer's feature extraction function, the loss can be improved with a minimum of 50 epochs. The Figure 8 graphs depict the level of loss and its comparison.

As a consequence, the findings have been analyzed using all of the tested values. When compared to earlier techniques, our hybrid model for image classification improves in accuracy and loss. The number of epochs in the hybrid model layers has been

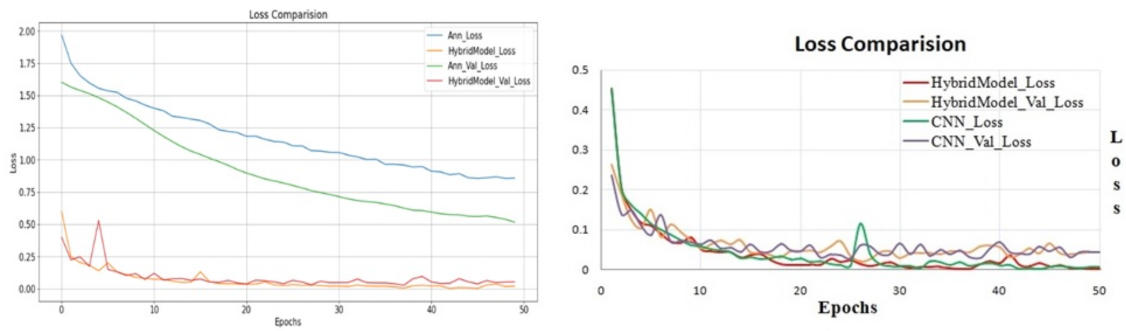

Fig 8. Loss Comparison of ANN, CNN with Hybrid Model

increased, resulting in more accurate data from the repository photos.

The performance analysis for the Medical dataset is shown in Figure 6 respectively. Compared to ANN and CNN, the proposed method has higher classification accuracy. As an illustration, the accuracy of the proposed hybrid technique for the medical dataset is 99.4%, which is high when compared to the accuracy of ANN and CNN, which are 97.79% and 98.78%, respectively.

The sample retrieved outcome of medical images from datasets is shown in the Figure 9. The medical images are retrieved in this case using an image retrieval method based on Euclidean distance. The Euclidean distance between the training image feature vector and the query image vector is computed. The retrieval accuracy is used to calculate the retrieval results of the suggested approach. The retrieval results are run for five distinct classes, like in classification.

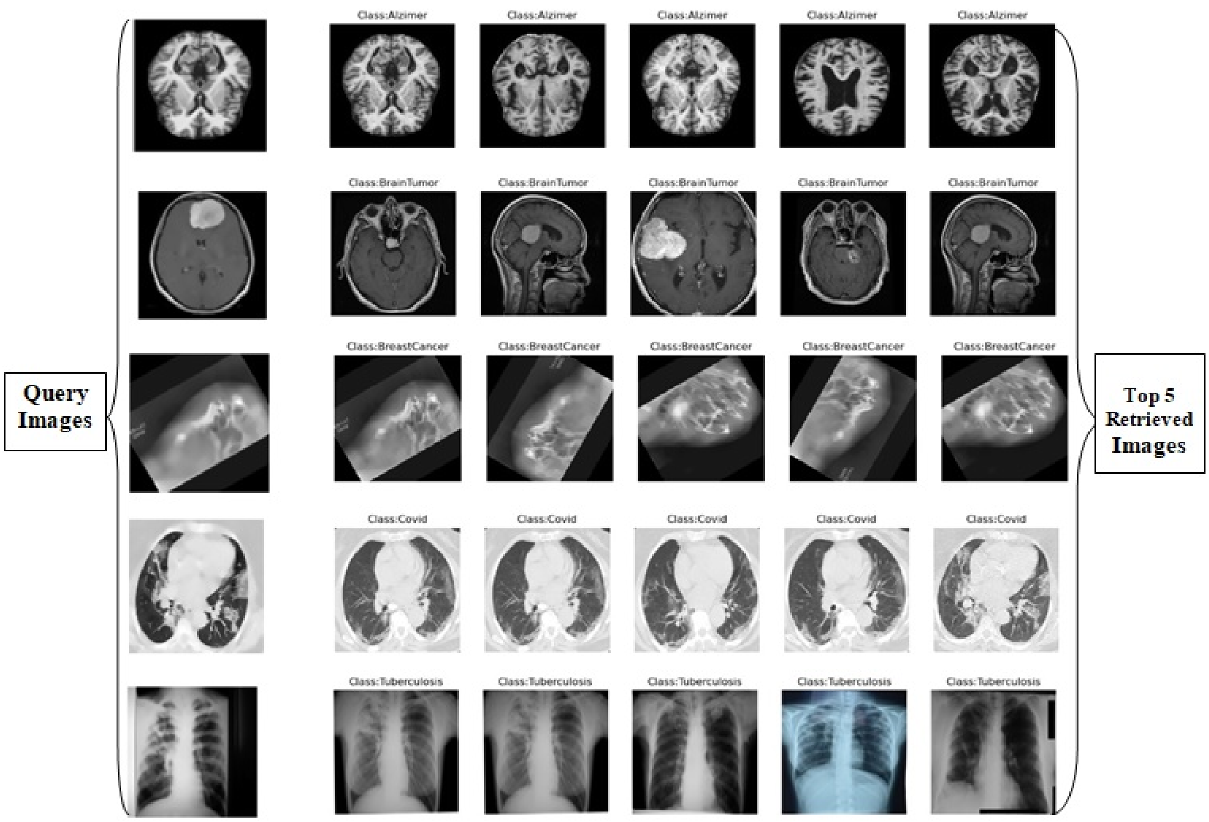

Fig 9. Screenshots illustrating the dataset's retrieval results

Table 3. Retrieval performances for Medical data set

Class#	Probability Score (%)
Class 1	100
Class 2	99.9
Class 3	99.88
Class 4	100
Class 5	100
AVG	**99.95**

The Probability Score for Medical datasets is shown in Table 3 and mainly considered to analyze the retrieval performances for Medical image datasets. The Figure 9 shows that the proposed method shows the relevant images retrieval in Medical datasets respectively, the Score for each class varies because of similar sizes of images are present in classes.

5 Results and Discussions

To put our proposed system to the test in a real-world medical setting, we must evaluate it. The first is efficiency, which refers to how quickly the system replies to user queries, and the second is effectiveness, which refers to how "good" the results are. The different models were trained, their accuracies and losses plotted, and the test accuracy was acquired and compared for 5 classes of medical datasets as shown in Table 2. We analyze parameters such as Accuracy, Precision, Recall, and F1-Score after performing CBIR on medical images. The proposed method's classification accuracy is compared to existing strategies to determine its effectiveness in medical picture retrieval. The existing methods used for discussions is VGG16[(1)], KNN's with GLCM[(2)], CNN[(18)], DeepSVM[(19)] etc. The Table 4 shows the comparison of the proposed model and existing work.

Table 4. Comparison of proposed model with existing works

Method	Dataset	Accuracy (%)
VGG16[(1)]	Computed tomography (CT)	97.6
KNN's With GLCM[(2)]	Chest CT images of COVID	98.9
Sparse Auto Encoder based DNN[(8)]	OASIS	95.34
ICNN[(9)]	Pap smear dataset	98.88
HoG-LTP method with CNN-Classifier[(10)]	CE-MRI	98.8
GIPBT + DKD[(11)]	Medical Image Set	98.4
CNN[(18)]	liver tumors CT images	96.55
CNN-based deep learning techniques - ResNet-18[(21)]	GPD data set	96.21
DeepSVM[(19)]	NCT-CRC-HE-100 K	98.75
Hybrid models (CNN, VGG16 and VGG19)[(16)]	diabetic retinopathy (DR)	90.6
CNN-sequential model[(20)]	Chest X-ray (1000 images)	98.437
Proposed Hybrid Model CNN-LSTM	**Medical Image Dataset**	**99.4**

The performance of ANN, CNN and Hybrid Model for the medical dataset considered in this work shown in Figure 6, the performance of proposed ensemble method provides more accuracy in image classification compared with ANN and CNN, because of more dense layers of CNN and additional layers of LSTM, also accurate feature extraction with GLCM. The existing works in[(1,2,9–11,16,18–21)] shown in Table 4, used various classification and features extraction methods. Compared with the existing works ours proposed Hybrid model provides better classification accuracy of 99.4% and also the retrieval probability score also calculated for various classes of medical images as shown in Table 3. Finally, Figure 9 shows that the proposed method retrieves relevant images from various classes of medical data set respectively. The high retrieval performances are due to Hybrid Model and Euclidean distance-based image retrieval across a wide range of images. Since then, the classification has been enhanced by employing appropriate feature extraction with GLCM.

6 Conclusion

In this study, we implemented content based image retrieval (CBIR) system for healthcare information using a most effective feature extraction method Grey Level Co-occurrence Matrix (GLCM); it is a well-known method for extracting characteristics from large picture archives. Artificial Neural Networks (ANN) and Convolution Neural Networks (CNN) are the most often utilized deep learning models for acquiring accurate pictures with low latency. These models are combined with a deep learning model based on Long-Short Term Memory (LSTM), which adds additional layers into its structure and operates on enormous datasets. When the testing results are compared to previous image classification methods, the accuracy levels improved. The loss ratio is also compared, and they are more accurate when image classification is conducted on big datasets. Once this model is capable of handling large datasets in real time, it will evict all other models in traditional deep learning approaches. The suggested hybrid model provides high accuracy image classification at a rate of 99.4% at a constant level, that is high compared to ANN and CNN and also the retrieval efficiency is good. In the future, the classification performance of the Healthcare images can be enhanced by using an ensemble feature selection method.

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