CINEFORUM
ISSN: 0009-7039
Vol. 65. No. 3, 2025

Integrating Mental Healthcare and Medical Image Processing Using ResNet, and DenseNet

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Abstract: The creation of a strong and effective data processing model catered for mental healthcare picture analysis is the main emphasis of this study. The technique starts with gathering pertinent picture data and then uses Huffman encoding to compress data to cut size. Advanced filtering methods help to remove noise from the compressed photos therefore guaranteeing high-quality data. The data is then divided in a 70:30 ratio into training and testing sets, therefore enabling a fair assessment of the performance of the model. The problem of over fitting is addressed using an Ensemble Model combining ResNet and DenseNet architectures, therefore guaranteeing that the model generalizes effectively to unseen data. Along with improved resistance against different cyber-attacks, the predicted results include shorter processing times, fewer error rates, and smaller packet sizes. The Proposed Ensemble Model achieved the highest Accuracy of 95.80%, Precision of 94.50%, Recall of 96.30%, F1-Score of 95.40% and minimum Time Consumption of 120s and Memory Usage of 350MB. Furthermore, the study seeks to enhance picture quality by means of noise filtering, thereby preserving the integrity of compressed data. With possible uses in real-time and resource-limited contexts, our study promises to improve the accuracy and security of mental healthcare picture analysis.

Keywords: Mental healthcare, Medical image processing, Huffman encoding, ResNet, DenseNet

1. Introduction

Research in combining AI with medical diagnostics to improve patient outcomes shows a major progress in current healthcare when mental healthcare and medical image processing are

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integrated. By means of precise and efficient feature extraction, deep learning models, especially CNNs have transformed medical image analysis. By examining medical pictures like MRI and CT scans, these models, which help to diagnose neurological diseases, brain abnormalities, and other mental health conditions, are very vital. While DenseNet increases feature propagation and lowers computing costs by reusing learnt features, ResNet solves the vanishing gradient issue and permits deeper network designs. Early identification, accurate diagnosis, and individualized treatment planning made possible by the integration of these AI-driven models in mental health care help to eventually enhance patient care. This multidisciplinary method closes the gap between psychiatry and medical imaging by using deep learning, therefore providing a more objective and data-driven evaluation of mental health disorders. The fast developments in AI and deep learning have transformed several disciplines, including medicine [1]. Mental healthcare, especially in the processing along with interpretation of medical pictures, is one of the important fields where these technologies are significantly changing. Accurate diagnosis is mostly dependent on picture data in mental health care; problems like depression, anxiety, along with other neurological diseases [2] are identified and monitored mostly by image data. Managing and processing vast amounts of picture data does, however, provide various difficulties including time consumption, error rates, and packet sizes, along with susceptibility to cyber-attacks [3]. This study endeavors to overcome these challenges by proposing an advanced data processing model that leverages Huffman-based compression, noise removal, and an Ensemble of ResNet and DenseNet architectures [4]. Mental healthcare is essential for diagnosing, treating, and managing mental problems and emotional well-being. [5]. It improves quality of life, mental resilience, and social and vocational functioning as well as symptoms. Psychotherapy, medication management, counselling, and community support are used in mental healthcare. Psychologists, psychiatrists, social workers, and counsellors collaborate to create individualized treatment regimens. Mental healthcare emphasizes early intervention, preventive interventions, and holistic care for psychological and social issues affecting mental health [6]. Mental healthcare is advancing with evidence-based approaches, technological advancements, and integrated care models. These innovations attempt to improve mental health support, lower stigma, and increase accessible for various communities [7]. This study is driven by the increasing need to improve the Accuracy along with efficiency of mental healthcare diagnosis. Given the rising worldwide frequency of mental health problems, more efficient

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methods to assist medical practitioners [8] are desperately needed. Although medical imaging offers important new perspectives on the anatomy along with operation of the brain, its huge volume could cause processing and analytical inefficiencies. By means of these models applied to neuroimaging data, such as fMRI or MRI scans, for example, one might identify biomarkers connected with mental health issues, therefore providing a more objective basis in case of diagnosis along with treatment [9]. From this mix, there are a few likely benefits. Among the probable benefits include early identification of mental health issues, more accurate tracking of therapeutic efforts, along with eventually better patient outcomes [10]. If these novel image processing techniques may provide light on the neurological foundations of mental health diseases, then better treatment outcomes in case of such diseases could be realistic. In all domains, ResNet along with DenseNet are very effective in integrating mental health with current medical image processing. This integration offers a data driven, more objective approach to comprehend along with manage mental health illnesses, hence transforming mental health diagnosis and treatment [11,12].

1.1 Contribution of the paper

- The importance of deep learning in the field of mental health is discussed in this study article.
- Attention has been drawn to the study methodology and limitations of the standard CNN, ResNet, and DenseNet methodologies in this paper's review.
- Additionally, this study offers a method for improved accuracy in mental disease identification through the use of an Ensemble model that takes into account the combination of ResNet and DenseNet.

1.2 Structure of the paper

The structure of the paper is as follows: Section 2 contains the literature review which helps the researcher to know earlier work done on this topic and used for better understanding and gathering data for future references. Section 3 contains the Research Gaps which highlights advancements in mental health treatment through technologies like virtual reality (VR), immersive interventions, and deep learning. Section 4 contains the Problem statement which describes the actual problem being faced in the diagnosis of mental health diseases. Datasets used in this study is mentioned in Section 5. The proposed work is mentioned in section 6.

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Section 7 contains experimental result analysis which has subgroups evaluating the result tables and graphs over the discussion of the efficiency of the work. Conclusion & Limitations of the research were concluded in Section 8 and Future Scope in Section 9.

2. Literature Review

Research into the detection and diagnosis of mental health conditions has benefited greatly from the expansion of Deep Learning technologies. Recent studies have investigated the feasibility of using these technologies to enhance the reliability and validity of mental health assessments. Over the last several years, researchers have been employing CNN-based models to extract valuable features from medical images in order to detect a variety of diseases and conditions, such as breast cancer, Parkinson's disease, Alzheimer's disease (AD), COVID-19, brain cancer, and heart disease. In terms of Accuracy, prior research indicated that models constructed using CNNs surpassed volumetric and conventional Machine Learning methods run by humans [13]. Individuals with Alzheimer's disease were categorised using a convolutional neural network (CNN) model that included diffusion-tensor imaging (DIO) and magnetic resonance imaging (MRI). Their study shows that when larger ROIs are employed with CNN architecture for classification, the size of the ROI in the hippocampus has no effect on the results of the classification. Utilising a data fusion approach and a six-layered convolutional neural network with a 48 × 48 × 48 ROI, their instance (AD-Normal Control) attained a commendable Accuracy of 96.7% [14]. It was originally necessary to differentiate the MRI image of white matter from grey matter. After that, they diagnosed AD using a Multiscale ConvNet (MSCNet). Their results imply that white matter, rather than grey matter, is the better indicator of Alzheimer's disease. Using the identical inputs, the ResNet-50 model obtains 96.01% and 95.88% Accuracy, whereas the MSCNet model with grey and white matter achieves 98.85% and 98.11% Accuracy, respectively. This is despite ResNet-50 having a lower standard deviation. According to their research, the CNN-based MSCNet model works well on the medical picture dataset with fewer parameters and less processing power [15]. The diagnosis of Alzheimer's disease was accomplished by utilising MRI scans in conjunction with Deep CNN and transfer learning models (VGG-16 and VGG-19). Contrarily, CNN outperformed VGG-19 in two performance metrics, AUC in three, and Accuracy, Computing Time, Precision, F-1 score, and Recall in one of six metrics. A self-generated dataset is computationally intensive, and this work does not employ one [16]. Convolutional neural

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networks (CNNs) were used to train the DensNet-201, Inception-ResNet-V2, and Inception-V3 models, which are able to detect skin lesion infections. In order to improve optimisation and take use of data augmentation, they ran the models through a battery of tests using several methodologies. On the ISIC 2019 dataset, their model achieved an optimised DenseNet-201 Accuracy of 93% and a data augmentation Accuracy of 98% on the HAM10000 dataset [17]. Xception, MobileNetV2, DenseNet-201, ResNetV2, InceptionV3, Visual Geometry Group (VGG-19), and InceptionResNetV2 were the seven CNN-based architectures that were used to develop the COVIDX-Net model for early COVID-19 patient identification. They found that the Inception model was the weakest performer, with a 50% Accuracy rate and an F1 score of 67 for normal cases and zero for COVID-19 instances. In terms of identifying instances that tested positive for COVID-19, the DenseNet-19 and VGG-19 models did an excellent job [18]. Using CT scan images, this research suggested a 3D-CNN architecture that could locate nonlinear 3D information regarding the lung nodule. The intrinsic structure of the CT scans was visualised using gradient class activation, which yielded further information. They competed with the top-tier AlexNet 2D-CNN and 3D-CNN models, using gradient-weighted class activation to attain a remarkable 97.17% classification Accuracy [19].

2.1 Comparison of Some Notable Research

In addition to the aforementioned studies, several others are also listed in Table 1.

Table 1. Comparison of Some Notable Research

References	Dataset	Technique	Conclusion	Limitation
[20]	Not specified	CNN	Proved CNN efficacy in medical image classification.	No detailed comparison with traditional methods.
[21]	Brain tumor MRI dataset	CNN	Achieved high Accuracy in brain tumor classification.	Limited generalization to other types of medical imaging.
[22]	Colon histopathological images	Custom CNN	Delivered accurate classification	Specific to colon histopathological images;

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			performance using custom CNN.	generalizability untested.
[23]	CT and X-ray dataset	Deep Learning Meta-classifier	Improved COVID-19 detection Accuracy using a meta-classifier.	Lack of longitudinal data and real-time validation.
[24]	COVID-19 and pneumonia datasets	Transfer Learning-based CNN	Enhanced performance in COVID-19 and pneumonia detection.	Focus on limited modalities and absence of cross-institutional validation.
[25]	MRI brain tumor dataset	Deep Transfer Learning	Demonstrated effectiveness of transfer learning in tumor classification.	No exploration of computational efficiency in real-world scenarios.
[26]	Chest X-ray dataset	Deep Transfer Learning	Provided a novel transfer learning approach for effective COVID-19.	Specific to chest X-rays; lacks multimodal data integration.
[27]	Various	Transfer Learning Models	Highlighted strengths and weaknesses of different transfer learning.	General analysis; no direct application to medical imaging.
[28]	Various	WOA Fused with SVM	WOA Fused with SVM	Not Specified
[29]	Various	Not Specified	Post COVID-19 depression.	Not Specified

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CINEFORUM
ISSN: 0009-7039
Vol. 65. No. 3, 2025

3. Research Gaps

The existing research highlights advancements in mental health treatment through technologies like VR, immersive interventions, and deep learning, yet significant gaps remain. Studies have explored VR's potential in clinical practice and adolescent mental well-being, but its integration into long-term mental health care strategies is underdeveloped. Similarly, deep learning methods, such as BERT, RoBERTa, and multimodal models, have shown promise in mental health detection via social media and EEG signals, but challenges like explainability, data quality, and cultural bias persist. The use of EEG for diagnosing mental disorders, while innovative, lacks robust models for multi-class classification and cross-modal integration. Furthermore, research on mental health applications in computational medicine and personalized treatment strategies remains fragmented, with limited focus on hybrid approaches combining VR, deep learning, and multimodal datasets. Despite efforts to classify and predict mental health conditions, scalability, generalization, and ethical considerations in deploying these technologies are insufficiently addressed, leaving room for comprehensive, integrative solutions.

4. Problem statement

Processing and analyzing massive amounts of image data has become difficult as mental healthcare relies more on image-based diagnosis. Large data quantities cause inefficiencies in current approaches, longer processing times, higher error rates, and more resource usage. Additionally compromising data quality along with resulting in incorrect diagnosis is medical image noise. Cyber-attacks include MITM brute force, along with SQL injection jeopardise patient privacy and data integrity in mental healthcare systems. Over fitting reduces the ability of DL models to extend across datasets. Therefore, to enhance mental healthcare diagnostics a strong along with effective data processing model that lowers data size, enhances picture quality, improves model performance, along with increases data security is required. Figure 1 below outlines challenges and solutions for processing image data in mental healthcare diagnostics.

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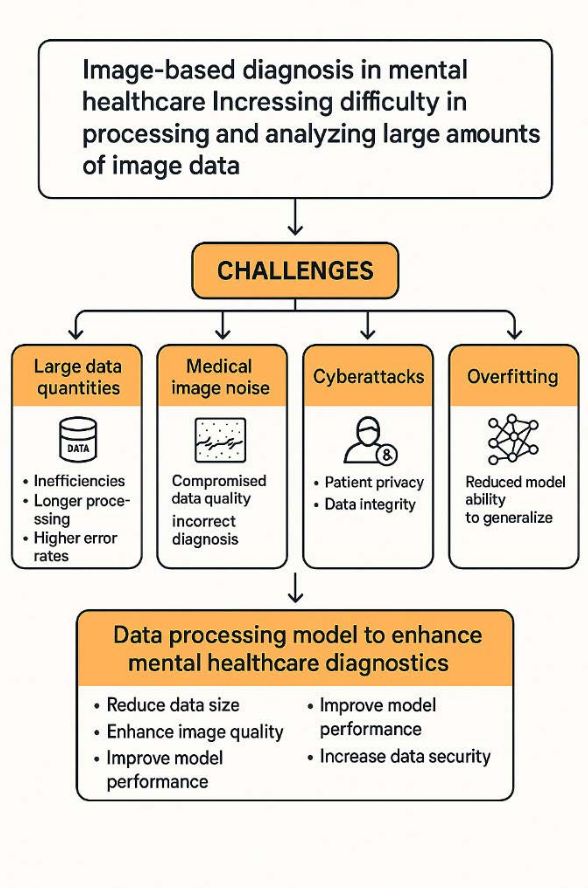

Fig 1. Optimized Diagnostic Framework

5. Datasets

There are several publicly available datasets that support research in image-based mental health analysis within the domain of mental healthcare image processing. The dataset utilized in this study is presented below, along with its corresponding URL:

Depression Datasets (Crowd sourced): This dataset contains images and other data related to mental health conditions like depression, collected through social media platforms and clinical studies [30].

6. Proposed Model

One suggests a sensible framework in case of managing the influence of visual stimuli on psychological well-being. It combines deep learning with modern compression along with noise reduction techniques in an attempt to provide a strong foundation in case of reliable picture analysis. The objectives of this method are optimal performance, shortened processing times, along with first-rate security. Combining ResNet and DenseNet topologies helps models

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to avoid over fitting and enable generalization from raw data. The initial phase is to gather pertinent pictures about mental health and arrange them for further studies. Huffman encoding lowers the data's size for simpler storage along with quicker processing, therefore marking the next stage in data compression. To maintain important information and improve picture quality after compression, the image is subjected to noise reduction methods include median or Gaussian filtering. Split cleaned and compressed data typically follows a 70:30 ratio into a training and testing set. This guarantees some in case of validation even when the model is trained on most of the data. Hyperparameter optimization is done before training using techniques such as random or grid search to target important parameters therefore enhancing performance of the model. Using the combined powers of ResNet and DenseNet, the suggested method centres on Ensemble model training along with testing. Training on the training set then testing on the testing set helps one assess the performance of the Ensemble model in mental healthcare image processing. Among the performance benchmarks assessed are Accuracy, Precision, and Recall, along with F1-score. Figure 2 illustrates the layers incorporated in the Proposed Model.

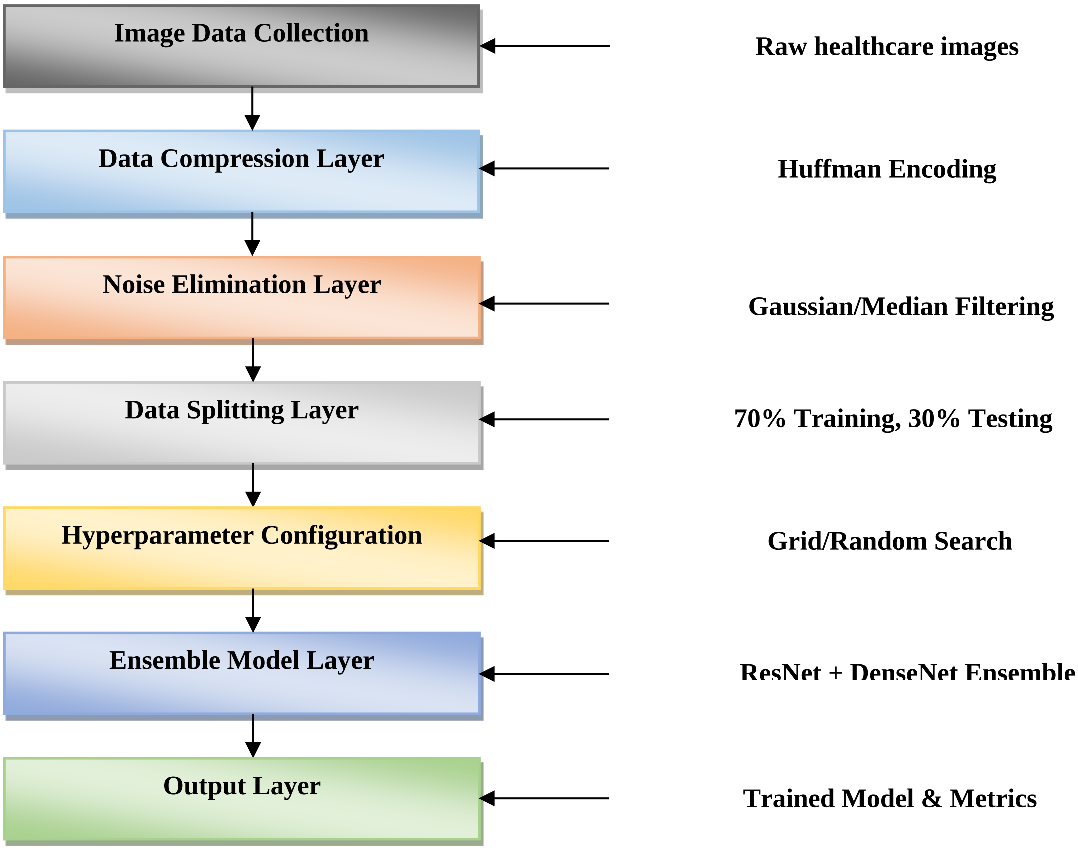

Fig 2. Proposed Model

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The initial phase of the process flow in case of this effort is gathering picture information on mental health. Data compression lowers data capacity after capture, therefore simplifying later on data processing. Decompression of data along with elimination of any noise comes next. This guarantees that the pictures are accurate and crisp along with helps to enhance the data quality. After then, the data is divided in a 70:30 ratio into training and testing sets, a common method meant to guarantee that the model gets trained on most of the data while saving some for validation. Hyperparameter settings are set to maximise model performance during training after data split. The study mainly consists on using an Ensemble model combining DenseNet and ResNet architectures. This dual strategy is especially selected to solve over fitting by using the strengths of both networks to raise the capacity of the model to generalize effectively on unavailability data. Using this Ensemble model, training and testing are then carried out hoping for strong and accurate findings in mental healthcare image analysis. In proposed Ensemble model combining DenseNet and ResNet architectures, the total number of layers is the sum of the layers in each individual model.

- DenseNet has layers organized in dense blocks, with models like DenseNet-121 (121 layers) or DenseNet-169 (169 layers).
- ResNet uses residual blocks, with models like ResNet-50 (50 layers) or ResNet-18 (18 layers).

Figure 3 illustrates a deep learning-based framework for efficient and secure mental healthcare image processing.

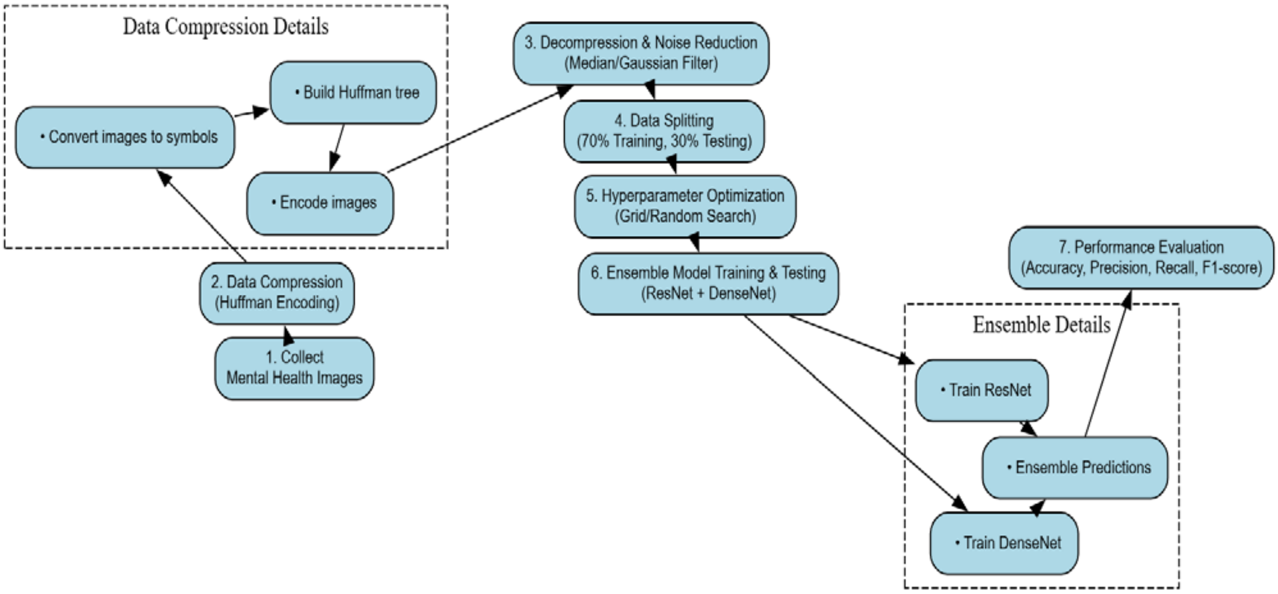

Fig 3. Optimized Pipeline for Mental Healthcare Image Analysis

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Step-by-Step Process with Algorithm

Step 1: Collect Image Data

- **Objective**: Gather relevant image data related to mental healthcare.
- **Action**: Curate a dataset containing images that are significant for mental healthcare analysis.

Step 2: Data Compression Using Huffman Encoding

- **Objective**: Compress the image data to reduce its size for efficient processing.
- **Algorithm:**
  1. **Input**: Original image data.
  2. **Process**:
     - Convert the image data into a sequence of symbols (pixels).
     - Calculate the frequency of each symbol.
     - Build a Huffman tree based on symbol frequencies.
     - Assign binary codes to symbols based on their position in the Huffman tree.
     - Replace symbols in the image with their corresponding binary codes.
  3. **Output**: Compressed image data.

Step 3: Noise Elimination from Compressed Data

- **Objective**: Remove noise from the compressed image data to improve its quality.
- **Algorithm**:
  1. **Input**: Compressed image data.
  2. **Process**:
     - Apply Gaussian or median filtering to the compressed data.
     - Identify and remove noise without losing essential details in the images.
  3. **Output**: Noise-free, compressed image data.

Step 4: Data Splitting

- **Objective**: Split the dataset into training and testing sets.
- **Algorithm**:
  1. **Input**: Noise-free, compressed image data.
  2. **Process**:
     - Randomly shuffle the data to ensure diversity.
     - Split the data into two subsets: 70% for training and 30% for testing.

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3. **Output**: Training set (70%) and testing set (30%).

Step 5: Hyperparameter Configuration

- **Objective**: Optimize the model's performance by configuring hyperparameters.
- **Algorithm**:
  1. **Input**: Training data.
  2. **Process**:
     - Select relevant hyperparameters such as learning rate, batch size, and number of epochs.
     - Perform grid search or random search to find the optimal hyperparameters.
  3. **Output**: Optimized hyperparameters.

Step 6: Training and Testing with Ensemble Model

- **Objective:** Train and test the model using an Ensemble of ResNet and DenseNet to prevent over fitting.
- **Algorithm:**
  1. **Input:** Training set, optimized hyperparameters.
  2. **Process:**
     - **Model Training:**
       - Initialize ResNet and DenseNet models.
       - Train both models on the training set using the configured hyperparameters.
       - Combine the predictions of both models to form the Ensemble.
     - **Model Testing**:
       - Test the Ensemble model on the testing set.
       - Evaluate the performance using metrics like Accuracy, Precision, Recall, and F1-score.
  3. **Output**: Trained Ensemble model and its performance metrics.

Pseudo code

Algorithm: Mental Healthcare Image Processing Model

Input: Image data related to mental healthcare.

Output: Trained Ensemble model, reduced time, error rate, packet size, and improved security.

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Step 1: Collect image data.

Step 2: Compress data using Huffman encoding.

a. Convert images to symbols.
b. Build Huffman tree.
c. Encode images.

Step 3: Remove noise from compressed data.

a. Apply Gaussian/median filter.

Step 4: Split data into 70% training and 30% testing sets.

Step 5: Configure hyper parameters.

a. Optimize using grid/random search.

Step 6: Train and test using ResNet and DenseNet Ensemble.

a. Train both models.
b. Ensemble their predictions.
c. Evaluate performance.

7. Result and Discussion

7.1 Performance Metrics

Several performance indicators, such as Accuracy, Precision, Recall, F1-Score, Time Usage, and Memory Usage, are used to assess the efficacy of the proposed Ensemble model that combines ResNet and DenseNet. The model's efficacy and efficiency can be better understood by examining each statistic separately. What follows is an explanation of these metrics along with their mathematical formulations.

7.1.1. Accuracy

The overall correctness of the model's predictions is measured by accuracy (%), a fundamental statistic. It is the proportion of occurrences (positive and negative) that were correctly classified as a percentage of the total instances in the dataset. In mathematics, precision is defined as:

$$Accuracy = \frac{TP+FN}{TP+TN+FP+FN} \qquad (1)$$

Where:

- True Positive (TP): Number of correctly predicted positive cases.
- True Negative (TN): Number of correctly predicted negative cases.

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- False Positive (FP): Number of incorrectly predicted positive cases (false alarms).
- False Negative (FN): Number of incorrectly predicted negative cases (missed detections).

7.1.2. Precision

The Positive Predictive Value, or Precision (%), is a measure of the percentage of positive cases that were accurately anticipated relative to all positive cases. Important areas where this is crucial include medical diagnosis and other areas where false positives can have serious implications. In medical settings, where patients may suffer needless treatments and stress due to erroneous positive diagnoses, a high Precision score indicates that the model produces fewer false positive errors. To determine Precision, one uses the following formula:

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

7.1.3. Recall (Sensitivity or True Positive Rate)

This parameter displays the Recall (%) for each model, which is the proportion of true positive occurrences that were accurately detected. Since missing good events could have major repercussions, recall (%) is critically crucial. One way to evaluate a model's performance is by looking at its recall, which is also called sensitivity or true positive rate. In early disease detection, for example, where false negatives can be rather expensive, it is incredibly valuable. By lowering the likelihood of missing important criteria, a high Recall value guarantees the detection of the majority of positive cases. It is necessary to strike a balance between Precision and Recall as improving the former usually reduces the latter. To determine Recall, one uses the following formula:

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

7.1.4. F1-Score

F1-Score provides a balanced measure of both Precision and Recall. It is the harmonic mean of these two metrics and is particularly useful when there is an uneven class distribution. The formula for the F1-Score is:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

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Models with F1-Scores closer to 1 are considered to have performed well. The score can take on values between 0 and 1.

7.1.5. Time Usage (Computation Time)

The usefulness of each model in real-world scenarios is assessed by this parameter. Training and testing times are also used to measure the model's efficiency. One way to express the overall time usage is:

$$T_{total} = T_{training} + T_{testing} \quad (5)$$

In cases when, The amount of time required to train the model with the dataset is denoted as Ttraining. The amount of time required to test the trained model on new data is called Ttesting. It is crucial to decrease processing time for real-time applications.

7.1.6. Memory Usage (Space Complexity)

One more important consideration when deploying models, especially for healthcare applications on a big scale, is memory efficiency. Here is the total amount of memory used by the model:

$$M_{total} = M_{model} + M_{data} + M_{cache} \quad (6)$$

The trained model parameters, including weights and biases, occupy Memory, denoted as Mmodel. With Mdata, both the input photos and the intermediate feature maps may be stored. During training, backpropagation and optimisation make use of Mcache, which is a temporary memory. Deploying the model on devices with limited resources, like embedded medical devices or mobile health monitoring systems, is made possible by optimising memory consumption.

7.2 Comparison of Performance Parameters

By carefully comparing the Proposed Model against current models, this section proves that the Proposed Model is effective. The proposed model is compared to other current models in Table 2 based on many metrics, including accuracy, precision, recall, computational time, memory use, F1-score, and more. As measured by the F1-score, recall, accuracy, and precision Table 2 displays the results comparing the various models to the Proposed Model (ResNet-DenseNet Ensemble). With an impressive Accuracy of 95.80%, it outperforms the individual ResNet (91.20%) and DenseNet (90.80%) models, demonstrating its exceptional picture

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categorisation capabilities. With a Precision of 94.50% and a Recall of 96.30%, the Proposed Model outperforms the alternatives in terms of Accuracy in accurately detecting positive and negative events, while producing fewer false positives and false negatives. The F1-score of 95.40% further supports the balanced performance of the model, which is excellent given the optimum trade-off between Accuracy and Recall. Compared to InceptionV3 and VGG16, which have lower Accuracy and F1-scores, the Proposed Model demonstrates a considerable improvement in performance metrics. Compared to VGG16 and InceptionV3, the model's competitive computational time is lower, which lends credence to its evaluation and training efficiency. The 350 MB required by the suggested model is lower than that of VGG16 (380 MB) and DenseNet (355 MB). The ResNet-DenseNet Ensemble Model improves Precision, Accuracy, and Recall while preserving memory economy and computing efficiency. This demonstrates that it is a viable alternative to Deep Learning in the field of Mental Health Image Analysis. A comparison of the suggested model's performance with other current models is shown in Table 2 below.

Table 2. Performance Comparison of Proposed Model with Other Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Time (s)	Memory Usage (MB)
Proposed Model (ResNet-DenseNet Ensemble)	95.80	94.50	96.30	95.40	120	350
ResNet	91.20	90.10	91.50	90.80	130	360
DenseNet	90.80	89.90	90.70	90.30	140	355
VGG16	88.60	87.50	88.20	87.80	150	380
InceptionV3	89.50	88.40	89.10	88.70	140	370

The performance of every model is measured in Accuracy, Precision, Recall, F1-score, Time, along with Memory Consumption. Combining ResNet and DenseNet in an Ensemble, the Proposed Model demonstrates better performance across all measures than single models including ResNet, DenseNet, VGG16, and InceptionV3. It is very economical in terms of computing Time and Memory Use. It also obtains the greatest Accuracy of 95.80%, Precision of 94.50%, Recall of 96.30%, and F1-Score of 95.40%. Figure 4 illustrates a graph depicting

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the comparative performance analysis of the proposed model relative to several benchmark models.

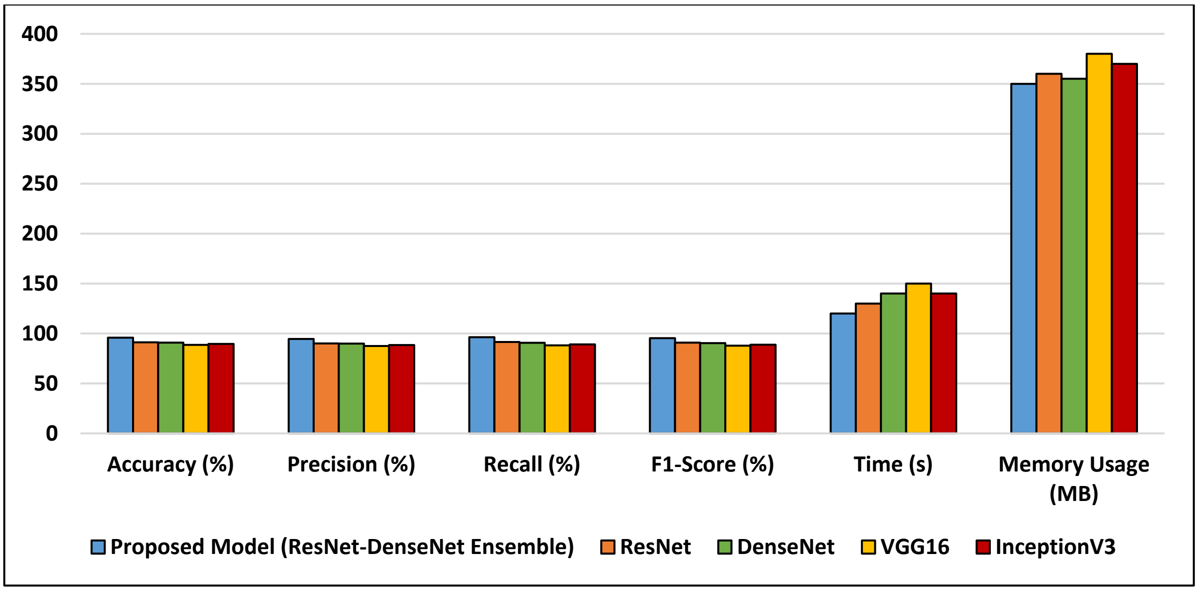

Fig 4. Performance Comparison of Proposed Model across different Models

Figure 5 graphically shows the Accuracy (%) of every model, therefore stressing their performance in precisely identifying pictures. Regarding accuracy, the Proposed Model ResNet-DenseNet Ensemble beats other models according to the graph. By means of a simple understanding of which model obtains the best accuracy of 95.80%, the visual comparison helps one understand the efficacy of every model in classification problems.

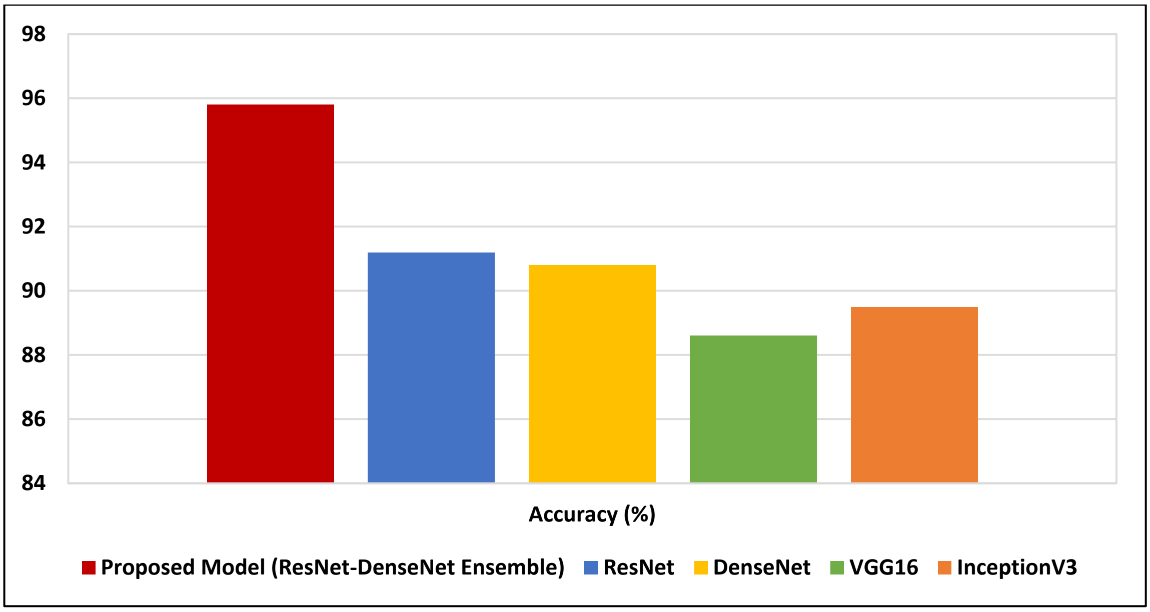

Fig 5. Comparison of Accuracy (%) across different Models

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Figure 6 shows every model's Precision (%)—that is, the percentage of actual positive predictions among all the positive predictions produced. With the maximum precision of 94.50% shown by the graph, the Proposed Model produces less false positive predictions than the others. Applications when reducing false positives depend on this.

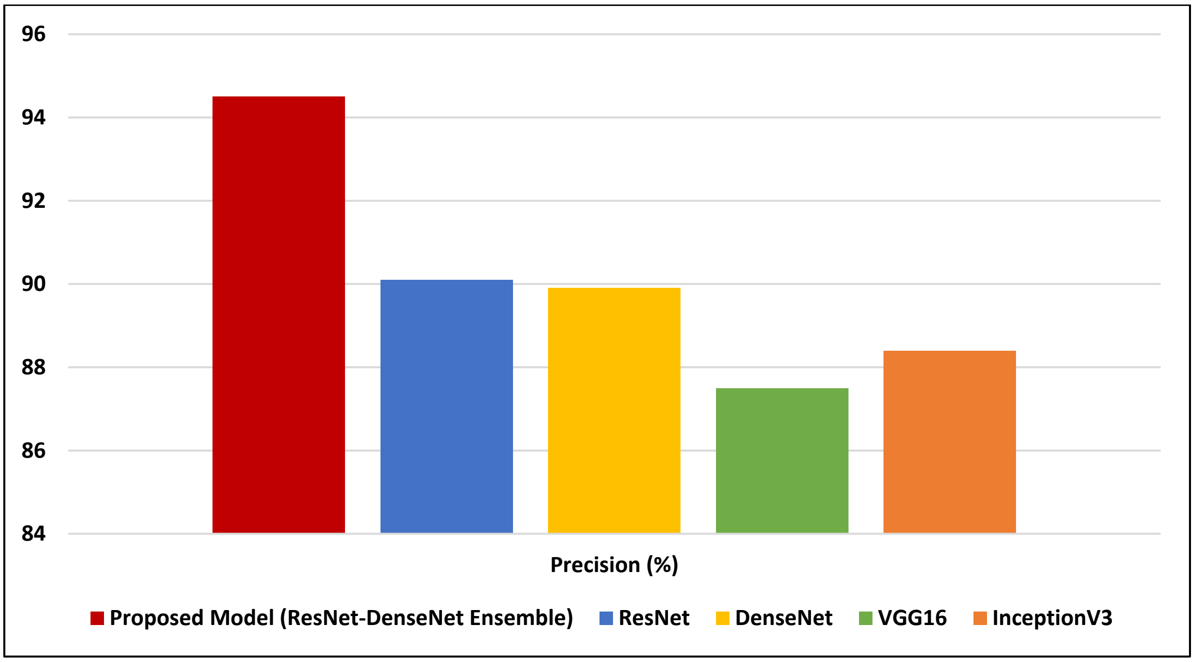

Fig 6. Comparison of Precision (%) across different Models

Figure 7 shows the Recall (%) for every model reflecting the proportion of actual positive occurrences that were precisely identified. The Proposed Model has the best recall of 96.30%, so it proves its accuracy in identifying positive occurrences based on the data.

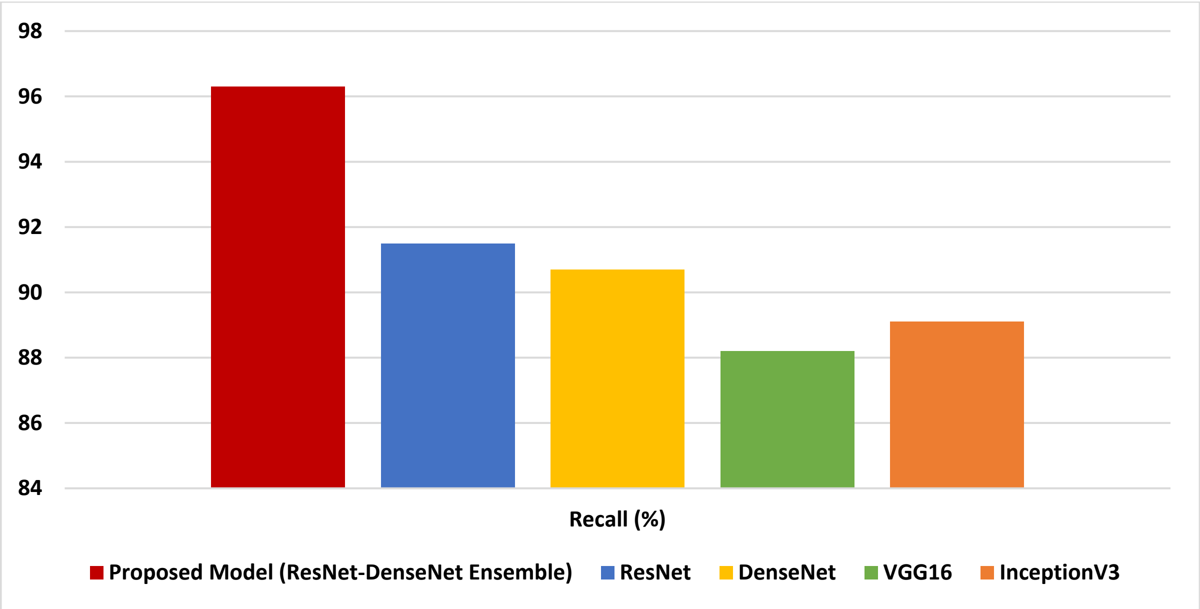

Fig 7. Comparison of Recall (%) across different Models

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Figure 8 shows the F1-Score (%) which strikes a mix between recall and accuracy. The Proposed Model is well-rounded in performance as its high F1-Score of 95.40% shows its capacity to preserve a decent trade-off between accuracy and recall.

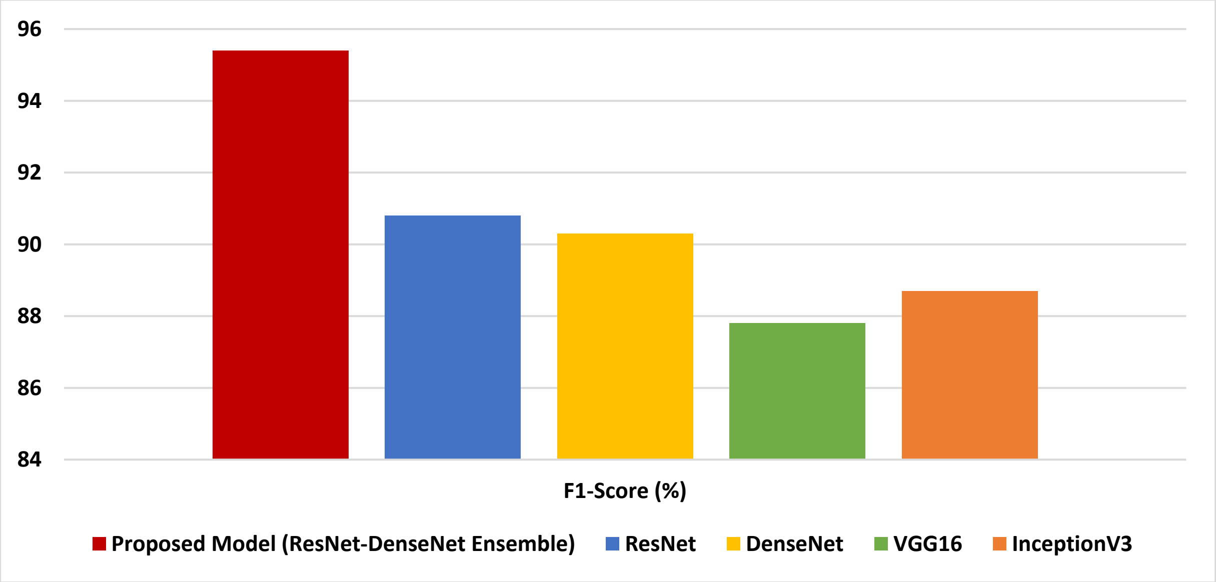

Fig 8. Comparison of F-1 Score (%) across different Models

Figure 9 shows every model's training and assessment time (s). The overall Time Consumption of the Proposed Model is 120s which is more time-efficient as compared to the other existing models as shown in the pie chart which qualifies for uses where fast processing is absolutely vital.

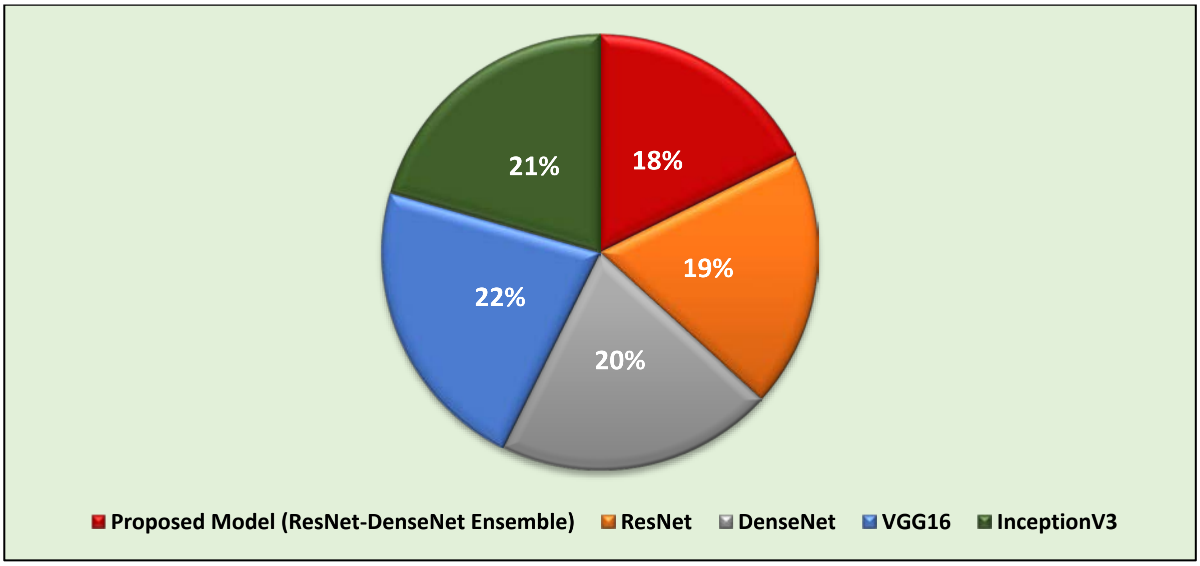

Fig 9. Comparison of Time (s) across different Models

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Figure 10 shows the Memory Usage (MB) of every model, therefore showing their respective training consumption of memory. Given its effectiveness in using computing resources, the Proposed Model shows a tolerable memory use of 350MB relative to the other existing models.

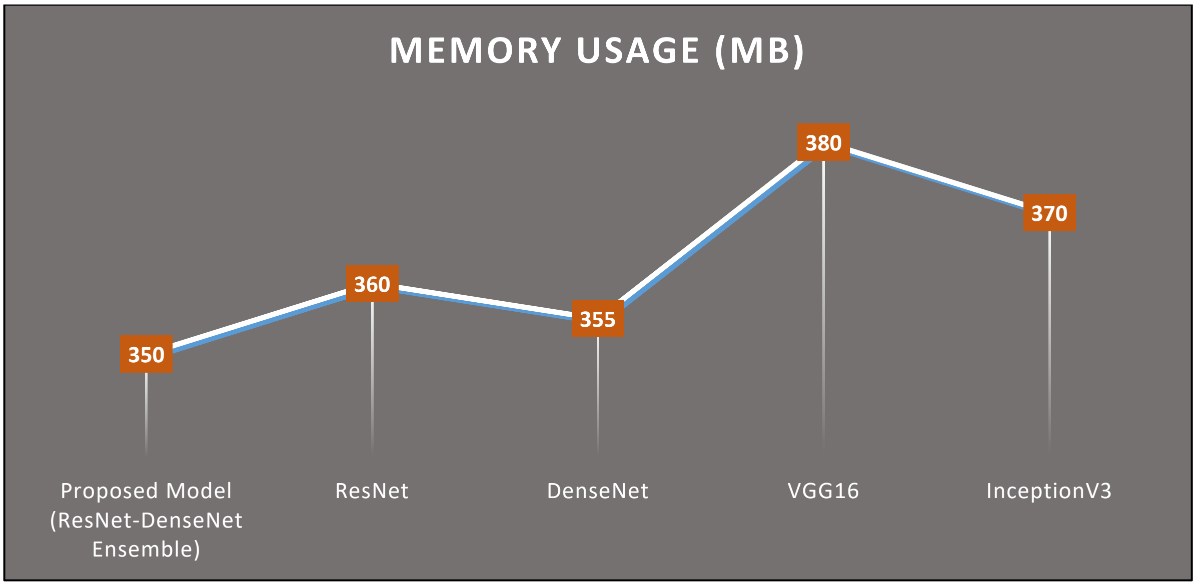

Fig 10. Comparison of Memory Usage (MB) across different Models

The results obtained along with the Table 2 taken together provide a complete picture of the performance criteria, therefore facilitating an educated comparison of the Proposed Model with other well-known models. This graphic depiction offers a constant view of the data and facilitates the understanding of how the performance of a model varies based on the criteria. Based on significant performance criteria, it offers a thorough comparison of many models. With the performance of the suggested model readily compared to other well-known models in terms of Accuracy, Precision, Recall, F1-score, Computational Time, and Memory Use, this graphical presentation enables one to grasp the strengths and shortcomings of each model.

8. Conclusion & Limitations

In order to overcome the challenge of processing and understanding massive volumes of mental healthcare picture data, this work develops a comprehensive data processing paradigm. A combination of ResNet and DenseNet topologies, coupled with Huffman-based compression and noise reduction, is introduced as a method to enhance the Precision, Efficiency, and security of mental healthcare assessments. By reducing Packet Sizes and Processing Time through data compression, the approach improves computing Efficiency in general. The Proposed Ensemble Model achieved the highest Accuracy of 95.80%, Precision of 94.50%, Recall of 96.30%, F1-Score of 95.40% and minimum Time Consumption of 120s and Memory

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Usage of 350MB. Improved data quality through noise reduction methods may lead to more precise diagnosis. In addition, the Ensemble Model aids in lowering over fitting, which enhances the model's ability to generalize to new data. According to the study's findings, robust security measures are required to protect patients' personal health information from various forms of cybercrime. The current approach faces several limitations, particularly in the realm of compression techniques, where achieving efficiency without compromising data security or quality remains a significant challenge. Additionally, noise patterns pose a considerable obstacle to improving visibility and data accuracy, making it difficult to ensure optimal data integrity. The work's findings aid in improving mental health care diagnosis and, by extension, patient outcomes through the use of more efficient image processing technologies.

9. Future scope:

There are numerous opportunities for future study and development in this area. One key direction involves the research and development of novel or hybrid compression techniques that enhance efficiency while preserving data security and quality. Advancing noise filtering algorithms, particularly adaptive ones, could significantly improve data visibility and accuracy. Additionally, strengthening security frameworks by incorporating more robust encryption methods and real-time threat monitoring could provide a more resilient defense against evolving cyber threats. The potential for real-time applications in dynamic environments, such as those encountered in IoT and edge computing, remains an exciting area for further exploration. Additionally, the integration of AI and machine learning technologies could lead to more flexible models capable of optimizing data processing based on the operating environment and data quality. These advancements are expected to significantly improve the efficiency, precision, and safety of mental healthcare diagnostics, making them adaptable to a broader range of healthcare settings.

ACKNOWLEDGMENT

The authors would like to acknowledge DST-FIST (Department of Computer Science & Engineering, Jamia Hamdard) No SR/FST/ET-11/2019/313(C) for providing the places where the study will be carried out. Another organisation that helped support our PhD program is the Visvesvaraya PhD Scheme for Electronics & IT, which is part of the MEITY (Ministry of Electronics and Information Technology) of the Indian government.

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REFERENCES

[1] Singha, R., &Singha, S. (2024). Mental health treatment. In Advances in medical technologies and clinical practice (pp. 91–110). IGI Global. https://doi.org/10.4018/979-8-3693-1123-3.ch006

[2] Bell, H., Nicholas, J., Alvarez-Jimenez, M., Thompson, A., &Valmaggia, L. (2020). Virtual reality as a clinical tool in mental health research and practice. Dialogues in Clinical Neuroscience, 22(2), 169–177. https://doi.org/10.31887/dcns.2020.22.2/lvalmaggia

[3] Hugh-Jones, S., Ulor, M., Nugent, T., Walshe, S., & Kirk, M. (2023). The potential of virtual reality to support adolescent mental well-being in schools: A UK co-design and proof-of-concept study. Mental Health & Prevention, 30, 200265. https://doi.org/10.1016/j.mhp.2023.200265

[4] Ionescu, A., Van Daele, T., Rizzo, A., Blair, C., & Best, P. (2021). 360° videos for immersive mental health interventions: A systematic review. Journal of Technology in Behavioral Science, 6(4), 631–651. https://doi.org/10.1007/s41347-021-00221-7

[5] Kumar, A., Kumari, J., & Pradhan, J. (2023). Explainable Deep Learning for Mental Health Detection from English and Arabic Social Media Posts. In ACM Transactions on Asian and Low-Resource Language Information Processing. Association for Computing Machinery (ACM).

[6] Ji, S., Zhang, T., Ansari, L., Fu, J., Tiwari, P., & Cambria, E. (2021). MentalBERT: Publicly Available Pretrained Language Models for Mental Healthcare. arXiv.

[7] Bokolo, B. G., & Liu, Q. (2023). Deep Learning-Based Depression Detection from Social Media: Comparative Evaluation of ML and Transformer Techniques. In Electronics (Vol. 12, Issue 21, p. 4396). MDPI AG. https://doi.org/10.3390/electronics12214396

[8] Lin, E., Sun, J., Chen, H., &Mahoor, M. H. (2024). Data Quality Matters: Suicide Intention Detection on Social Media Posts Using a RoBERTa-CNN Model (Version 1). arXiv. https://doi.org/10.48550/ARXIV.2402.02262

[9] Rivera, M. J., Teruel, M. A., Maté, A., Trujillo, J.: Diagnosis and prognosis of mental disorders by means of EEG and deep learning: a systematic mapping study. Artificial Intelligence Review 55(2), 1209–1251 (2021).

[10] Abdelhameed, A. M., Bayoumi, M.: Semi-Supervised EEG Signals Classification System for Epileptic Seizure Detection. IEEE Signal Processing Letters 26(12), 1922–1926 (2019).

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[11] Acharya, U. R., Sree, S. V., Chattopadhyay, S., Suri, J. S.: Automated Diagnosis Of Normal And Alcoholic EEG Signals. International Journal of Neural Systems 22(03), 1250011 (2012)

[12] Acharya, U. R., Oh, S. L., Hagiwara, Y., Tan, J. H., Adeli, H.: Deep Convolutional Neural Network for the Automated Detection and Diagnosis of Seizure Using EEG Signals. Computers in Biology and Medicine 100, 270–278 (2018). 0 20 40 60 80 100 120 10 20 30 40 50 60 70 80 90 100 Time Taken in Sec Epoch Conventional Approach Proposed Work 13

[13] Khvostikov, A.; Aderghal, K.; Benois-Pineau, J.; Krylov, A.; Catheline, G. 3D CNN-based classification using sMRI and MD-DTI images for Alzheimer disease studies. arXiv 2018, arXiv:1801.05968, preprint.

[14] Liu, Z.; Lu, H.; Pan, X.; Xu, M.; Lan, R.; Luo, X. Diagnosis of Alzheimer's disease via an attention-based multi-scale convolutional neural network. Knowl. Based Syst. 2022, 238, 107942.

[15] Ajagbe, S.A.; Amuda, K.A.; Oladipupo, M.A.; Afe, O.F.; Okesola, K.I. Multi-classification of alzheimer disease on magnetic resonance images (MRI) using deep convolutional neural network (DCNN) approaches. Int. J. Adv. Comput. Res. 2021, 11, 51–60.

[16] Villa-Pulgarin, J.P.; Ruales-Torres, A.A.; Arias-Garz, D.; Bravo-Ortiz, M.A.; Arteaga-Arteaga, H.B.; Mora-Rubio, A.; Alzate-Grisales, J.A.; Mercado-Ruiz, E.; Hassaballah, M.; Orozco-Arias, S.; et al. Optimized Convolutional Neural Network Models for Skin Lesion Classification. Comput. Mater. Contin. 2022, 70, 2131–2148.

[17] Hemdan, E.E.-D.; Shouman, M.A.; Karar, M.E. COVIDX-Net: A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-ray Images. arXiv 2020, arXiv:2003.11055. preprint. [

[18] Horry, M.J.; Chakraborty, S.; Paul, M.; Ulhaq, A.; Pradhan, B.; Saha, M.; Shukla, N. COVID-19 Detection through Transfer Learning Using Multimodal Imaging Data. IEEE Access 2020, 8, 149808–149824.

[19] Joshua, E.S.N.; Bhattacharyya, D.; Chakkravarthy, M.; Byun, Y.-C. 3D CNN with Visual Insights for Early Detection of Lung Cancer Using Gradient-Weighted Class Activation. J. Healthc. Eng. 2021, 2021, 6695518.

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[20] Li, Q.; Cai, W.; Wang, X.; Zhou, Y.; Feng, D.D.; Chen, M. Medical image classification with convolutional neural network. In Proceedings of the 2014 13th International Conference on Control Automation Robotics & Vision (ICARCV), Singapore, 10–12 December 2014; pp. 844–848.

[21] Tiwari, P.; Pant, B.; Elarabawy, M.M.; Abd-Elnaby, M.; Mohd, N.; Dhiman, G.; Sharma, S. CNN Based Multiclass Brain Tumor Detection Using Medical Imaging. Comput. Intell. Neurosci. 2022, 2022, 1830010.]

[22] Yildirim, M.; Cinar, A. Classification with respect to colon adenocarcinoma and colon benign tissue of colon histopathological images with a new CNN model: MA_ColonNET. Int. J. Imaging Syst. Technol. 2021, 32, 155–162.

[23] Ravi, V.; Narasimhan, H.; Chakraborty, C.; Pham, T.D. Deep learning-based meta-classifier approach for COVID-19 classification using CT scan and chest X-ray images. Multimed. Syst. 2021, 28, 1401–1415.]

[24] Chakraborty, S.; Paul, S.; Hasan, K.M.A. A Transfer Learning-Based Approach with Deep CNN for COVID-19- and Pneumonia-Affected Chest X-ray Image Classification. SN Comput. Sci. 2021, 3, 17.

[25] Srinivas, C.; Prasad, N.K.S.; Zakariah, M.; Alothaibi, Y.A.; Shaukat, K.; Partibane, B.; Awal, H. Deep Transfer Learning Approaches in Performance Analysis of Brain Tumor Classification Using MRI Images. J. Healthc. Eng. 2022, 2022, 3264367.

[26] Kumar, N.; Gupta, M.; Gupta, D.; Tiwari, S. Novel deep transfer learning model for COVID-19 patient detection using X-ray chest images. J. Ambient. Intell. Humaniz. Comput. 2021, 14, 469–478.]

[27] Vijaysinh, L. A Comparison of 4 Popular Transfer Learning Models. AIM 2021. Available online: https://arxiv.org/abs/1603.08631 (accessed on 23 February 2023).

[28] Rao, H., Gupta, M., Agarwal, P., Bhatia, S., Bhardwaj, R.: Mental health issues assessment using tools during COVID-19 pandemic. Innovations in Systems and Software Engineering 12, 1-12 (2022).

[29] Gupta, R., Alam, M. A., & Agarwal, P.: Whale Optimization Algorithm Fused with SVM to Detect Stress in EEG Signals. Intelligent Decision Technologies 15(1), 87–97 (2021).

[30] URL: https://www.kaggle.com/datasets/arashnic/the-depression-dataset

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