

Deep Learning-Based Alzheimer's Risk Classification Using Inception V3 And Mri Data

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Cite this paper as: Dr. A Manjula, Dr. K Vaishali, Dr. N Swapna, Dr. Venkateswarlu B (2024). Deep Learning-Based Alzheimer's Risk Classification Using Inception V3 And Mri Data. *Frontiers in Health Informatics*, 13 (8) 579-590

ABSTRACT

Alzheimer's disease is a progressive neurological illness that impairs memory, thinking, and day-to-day functioning. It has a significant negative influence on people and is becoming a bigger problem for healthcare systems worldwide. Determining Alzheimer's risk levels accurately and promptly is essential for starting early therapies that can decrease the disease's course and enhance quality of life. Conventional diagnostic techniques, such as clinical assessments and manual brain imaging analysis, are often laborious, arbitrary, and vulnerable to variation. In this work, we suggest an automated approach that uses a state-of-the-art convolutional neural network and the Inception V3 algorithm to categorize Alzheimer's risk into four groups: Moderately Demented, Very Mild Demented, Mild Demented, and Non Demented. To ensure strong model performance, the system is trained using a dataset of 6,400 MRI images that have been preprocessed to improve features and reduce noise. The Inception V3 model is refined to capture minor patterns in brain areas linked to various stages of Alzheimer's disease via transfer learning methods. The suggested model outperforms several current deep learning frameworks and conventional diagnostic techniques with an outstanding 98.6% accuracy rate in risk-level categorization. This technology greatly improves dependability and reduces diagnostic delays by automating the interpretation of complicated medical imaging data, assisting medical practitioners in making well-informed judgments. This work demonstrates the revolutionary potential of deep learning in Alzheimer's disease risk assessment and early detection, opening the door for scalable, reasonably priced diagnostic tools in clinical practice.

Index Terms: Alzheimer's disease, **Neurodegenerative Disorder, Medical Imaging, Early Detection**, Inception V3 algorithm, Medical Imaging, Early Detection, **Diagnostic Automation**.

1. INTRODUCTION

Millions of people worldwide suffer from Alzheimer's disease (AD), a chronic and progressive neurological illness that causes behavioral abnormalities, memory loss, and cognitive decline. About 60–80% of dementia cases worldwide are caused by it, making it the most prevalent cause of dementia [1]. Alzheimer's disease is predicted to become much more common as the population ages, which will provide considerable problems for caregivers and healthcare systems [2]. Early Alzheimer's disease identification is essential for putting in place prompt therapies that may slow the illness's course and enhance the lives of those who are impacted [3]. Clinical assessments, cognitive testing, and analysis of brain imaging data from magnetic resonance imaging (MRI) are examples of traditional diagnostic techniques. However, these

approaches might result in inconsistent diagnoses since they are often subjective, time-consuming, and dependent on the knowledge of medical experts [4].

The processing of medical imaging data might undergo a significant transformation thanks to recent developments in deep learning and artificial intelligence (AI) [5]. In healthcare applications, convolutional neural networks (CNNs) in particular have become very effective tools for feature extraction and picture categorization [6]. Known for its depth and computational efficiency, Inception V3 is one of these models that has shown remarkable success in challenging picture analysis tasks [7].

The goal of this project is to create an automated system for MRI scan-based Alzheimer's risk level classification by using Inception V3's capabilities. Patients are divided into four risk categories by the model: Moderately Demented, Very Mild Demented, Mild Demented, and Non Demented. The suggested solution tackles important issues including class imbalance and feature extraction by using a dataset of 6,400 labeled pictures, guaranteeing good accuracy and dependability [8].

Developing a reliable and scalable method for Alzheimer's disease risk assessment and early diagnosis is the main goal of this project. In addition to cutting down on diagnostic delays, this method provides trustworthy insights to medical practitioners, facilitating more efficient treatment planning [9]. The study's findings highlight the possibility for better illness management via the integration of AI-driven solutions into clinical processes.

Comparison Between a Normal Brain and an Alzheimer's-Affected Brain

The human brain is an extremely intricate organ that governs every body function and makes cognitive activities like remembering, reasoning, and decision-making possible. The anatomy of a normal brain is undamaged, with distinct grooves (sulci) and folds (gyri). Given the active neuronal connections necessary for optimal functioning, the brain tissue seems thick and healthy. The brain's tiny, proportional ventricles, which are fluid-filled chambers, preserve the structural integrity of the brain. On the other hand, when neurons and synapses gradually go, the brain of a person with Alzheimer's disease experiences severe deterioration. The most obvious sign of this degradation is brain atrophy, which is the decrease of brain tissue. The reduction of brain volume is shown by the sulci widening and the gyri becoming narrower. The atrophy of the surrounding brain tissue also causes the ventricles to expand. The buildup of tau protein tangles and beta-amyloid plaques, which impair neuron function and ultimately cause cell death, is what causes these structural alterations. These changes have a significant effect on cognitive and functional skills, including language, memory, and reasoning—all of which are characteristic signs of Alzheimer's disease.

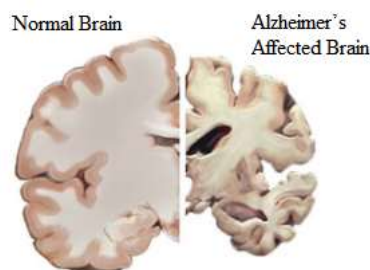


Figure .1 Brain Image

II.LITERATURE REVIEW

- Sisodia et al. [1] examined deep transfer learning techniques for MRI image-based Alzheimer's disease prediction. Their research demonstrated the efficacy of class-wise prediction techniques and emphasized how deep learning models may identify patterns in neuroimaging data. Key obstacles were highlighted by the research, such as the need for different datasets and computing costs, and solutions were presented.

The VGG-TSwinformer, a transformer-based deep learning model designed for Alzheimer's disease early detection, was presented by Hu et al. [2]. By combining transformer topologies with VGG characteristics, the suggested model was able to detect early symptoms from MRI scans with excellent accuracy. The potential of transformers for managing intricate medical picture data was also covered in the research.

Sethi et al. [3] investigated the use of convolutional neural networks (CNNs) for Alzheimer's disease categorization. Preprocessing procedures and CNN layers for feature extraction and classification were part of their technique. Despite acknowledging limits in generalizability across datasets, the research showed the promise of CNNs for illness diagnosis.

A modular machine learning architecture for Alzheimer's disease classification utilizing retinal vasculature data was suggested by Tian et al. [4]. The work demonstrated the possibility of non-invasive retinal scans as a diagnostic tool for neurodegenerative illnesses by using sophisticated image processing methods and modular machine learning algorithms.

An extensive study of machine learning methods for Alzheimer's disease diagnosis was carried out by Tanveer et al. [5]. They discussed the benefits and drawbacks of supervised, unsupervised, and ensemble approaches in their study. The need of dependable and interpretable machine learning models for medical applications was also emphasized by the review.

Layer-wise relevance propagation (LRP) was used by Böhle et al. [6] to explain the choices made by deep neural networks in the categorization of Alzheimer's disease based on MRI. Their research highlighted the significance of comprehending neural network activity in crucial healthcare applications and offered insights on model interpretability.

A graph convolutional network (GCN)-based method for illness prediction was presented by Parisot et al. [7], with applications to Alzheimer's disease and autism spectrum disorder. The work provided a fresh viewpoint on medical graph analytics by showcasing the potential of GCNs to use patient relationship data in illness detection.

An Alzheimer's diagnostic method based on independent component analysis-support vector machine (ICA-SVM) was created by Khedher et al. [8]. Their study showed the efficacy of integrating ICA with SVM for high-dimensional data categorization and provided visual aids for better interpretability.

The use of transfer learning to the categorization of Alzheimer's disease was investigated by Hon and Khan [9]. By fine-tuning pre-trained neural networks using MRI datasets, their method showed promise in identifying the phases of illness development. The advantages of transfer learning in resolving issues with limited datasets were highlighted in the research.

Using fMRI data, Sarraf and Tofghi [10] used deep learning convolutional neural networks (CNNs) to categorize Alzheimer's illness. Preprocessing, feature extraction, and classification were all part of their approach, which produced noticeably higher accuracy than conventional techniques. The research demonstrated CNNs' potential for illness identification based on neuroimaging.

III.PROBLEM STATEMENT

A neurological condition that worsens over time, Alzheimer's disease (AD) severely affects memory, cognition, and day-to-day functioning. It is the most prevalent kind of dementia, and as the world's population ages, its incidence is predicted to increase significantly over the next few decades. Effective intervention and management of Alzheimer's disease depend on early detection since it enables medicines that may halt the illness's course and enhance patients' quality of life. However, conventional diagnostic techniques—like cognitive testing, clinical assessments, and professional examination of brain imaging scans are often laborious, arbitrary, and prone to human error. These difficulties show that more precise, effective, and scalable solutions are required.

Automated study of medical imaging, especially MRI scans, holds great promise for improving the early diagnosis of Alzheimer's disease with the advent of artificial intelligence (AI) and deep learning methods. Automated methods that can reliably categorize Alzheimer's risk levels throughout a range of phases, from non-demented to very mild, mild, and moderately demented, are still lacking, however.

The objective of this study is to create an AI-based system that automatically classifies Alzheimer's disease risk levels using the Inception V3 deep learning algorithm. Four categories—Non Demented, Very Mild Demented, Mild Demented, and Moderate Demented—will be used by the algorithm to categorize MRI pictures. This system will make use of sophisticated picture feature extraction and transfer learning to precisely identify small alterations in brain structures that are suggestive of Alzheimer's disease at different stages. The system will use the pre-trained Inception V3 model.

IV. PROPOSED MODEL The suggested approach uses deep learning methods, notably the Inception V3 algorithm, to automate the categorization of Alzheimer's disease risk levels. Four categories will be used by this model to categorize brain MRI scans: non-demented, very mildly demented, mildly demented, and moderately demented. Key issues in Alzheimer's diagnosis, including the unpredictability of conventional diagnostic techniques, the need for more effective and scalable solutions, and the difficulty of interpreting MRI scans for minute alterations in brain anatomy, are addressed by the model.

High-level characteristics will be extracted from the MRI images using Inception V3, a deep convolutional neural network renowned for its effectiveness and precision in image classification tasks. Through the use of transfer learning, the model can identify generic patterns using pre-trained weights from ImageNet. These patterns may then be adjusted to highlight characteristics unique to Alzheimer's-related brain alterations. In order to address the issue of class imbalance in the dataset and guarantee that the model can generalize well across all four phases of dementia, the model will also use data augmentation approaches.

The model will be taught to accurately categorize brain scans, offering an automated option that speeds up diagnostics, helps doctors discover Alzheimer's early, and guarantees consistency in determining risk levels. By making the diagnostic process more scalable, dependable, and accessible in clinical settings, this method seeks to enhance it overall.

V.SYSTEM MODEL

Researchers have created automated algorithms to evaluate brain MRI scans and categorize individuals into different phases of the illness by using advances in deep learning. The Alzheimer's disease workflow is shown in the following figure.

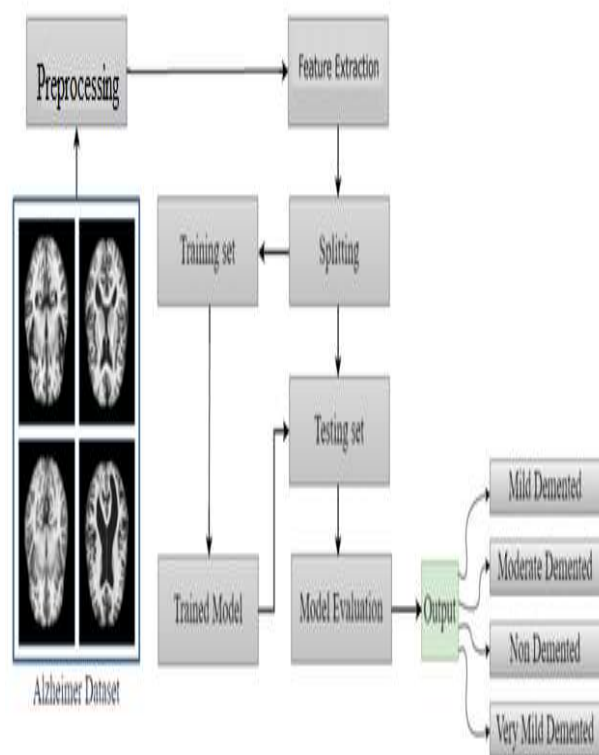


Figure2.System Model for Alzheimer's disease Classification

A methodical framework for classifying MRI scans of Alzheimer's disease is shown in figure (2). Preprocessing is the first step, during which the dataset is made ready by improving the consistency and quality of the images. After that, feature extraction finds important patterns that are pertinent to the diagnosis of Alzheimer's. After that, the data is divided into a Testing Set for performance assessment and a Training Set for model development. Machine learning methods are used to generate a trained model, which is then evaluated using Model Evaluation metrics. Patients are categorized as non-demented, very mildly demented, mildly demented, and moderately demented in the final output. This method guarantees effective and precise disease staging for early identification and treatment. For picture classification and recognition, we used the Inception V3 method, which provides excellent accuracy and maximizes processing efficiency.

VI.IMPLEMENTATION METHODS

a.Dataset Description

MRI or brain imaging scans that have been divided into four groups according to Alzheimer's risk levels make up the dataset utilized in this research. To guarantee a reliable assessment of the model, the dataset is separated into subsets for training and testing. The data distribution is shown below:

Category	Training Samples	Testing Samples
Mild Demented	717	179
Moderate Demented	52	12
Non Demented	2560	640
Very Mild Demented	1792	448

Table 1. Alzheimer's Dataset Details

Gathering a suitable dataset of brain MRI images is the first stage in putting the Alzheimer's disease classification algorithm into practice. Four different Alzheimer's risk levels—Non Demented (ND), Very Mild Demented (VMD), Mild Demented (MD), and Moderate Demented (MOD)—are represented in the dataset used for this experiment. The ADNI (Alzheimer's Disease Neuroimaging Initiative) and other publicly accessible medical image collections that provide labeled MRI scans for research purposes are the sources of these pictures. For the model to be able to manage changes in imaging circumstances, patient demographics, and illness stages, the dataset has to be sufficiently vast and varied.

b.Preprocessing:

Preprocessing the MRI pictures comes next once the dataset has been gathered. To make sure the data is in the right format for the model to train efficiently, there are a number of stages involved. Since the Inception V3 model requires a constant input size, the MRI images are usually reduced to a standard size (for example, 299x299 pixels). In order to facilitate quicker convergence during training, the pictures are also normalized to guarantee that pixel values fall within a predetermined range, usually [0, 1]. The training pictures are also subjected to data augmentation methods including zooming, flipping, and random rotations. By increasing the dataset's variety, these augmentations strengthen the model and lessen overfitting. After that, the data is divided into training, validation, and testing sets. The model is trained using the training set, hyperparameter tweaking is done with the validation set, and model assessment is done with the test set.

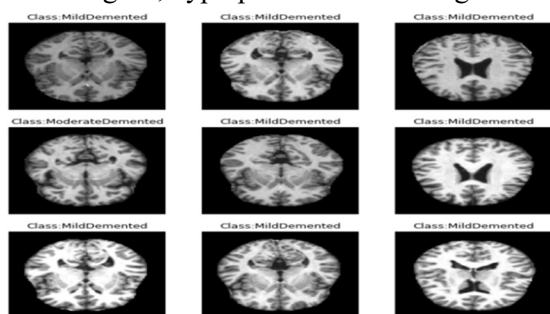


Figure 3. Preprocessing Data

A collection of brain MRI scans classified under various Alzheimer's disease classifications is shown in Figure 3, with one image being classified as "Moderate Demented" and the remainder falling into the "Mild Demented" group. The preprocessing stage, which involves resizing and normalizing the pictures in order to get them ready for training, produces these scans. Every scan reveals unique structural brain patterns that help distinguish between Alzheimer's disease development stages.

c.Feature Extraction:

The pre-trained Inception V3 model is used in this stage to extract features. Automatically learning hierarchical features from photos, Inception V3 is a deep convolutional neural network (CNN) that starts with low-level features (textures, edges) and progresses to high-level patterns (objects, forms). The model has previously been trained on a large and varied dataset (ImageNet), which has taught it to recognize a variety of picture attributes that are also helpful for

MRI scan classification. Transfer learning involves adapting the weights of the pre-trained model to the new dataset, with just the end layers being trained for Alzheimer's classification and the early layers frozen to preserve learnt characteristics. The model produces feature maps, which show various patterns seen in the pictures, such alterations in the structure of the brain that could be a sign of the advancement of Alzheimer's disease.

d.Model Generation:

To customize the network for the particular job of Alzheimer's disease risk classification, a custom classifier is added after feature extraction using the pre-trained Inception V3 model. The Flatten layer of the custom classifier converts the 3D feature maps from the Inception V3 model into a 1D vector. In order to get from convolutional layers to fully linked layers, this flattening phase is required. The Dense layer, which uses the ReLU activation function and has 1024 neurons, is the next stage. This layer aids in the model's learning of intricate, non-linear connections between the risk categories for Alzheimer's disease and the retrieved variables. The dense layer is followed by a Dropout layer with a 50% dropout rate to prevent overfitting and improve generalization. In order to prevent the model from becoming too dependent on any one feature, dropout helps to randomly deactivate individual neurons during training. Lastly, the output layer generates probabilities for each of the four Alzheimer's risk categories Non Demented, Very Mild Demented, Mild Demented, and Moderate Demented using the softmax activation function. The multi-class classification job is handled by training the model with categorical cross-entropy loss, and model parameters are effectively optimized using the Adam optimizer. A training dataset is utilized in the training process, and a validation set is used to track performance and adjust hyperparameters such as batch size and learning rate for best outcomes.

e.Model Architecture

Our model's design makes use of the Inception V3 convolutional neural network (CNN), which is perfect for image classification tasks, including medical imaging such as MRI scans for Alzheimer's disease, due to its depth and efficiency in extracting complicated data.

1.Pre-trained Inception V3 Model

The model's foundation is the Inception V3 architecture. The model has previously learnt a number of generic characteristics, including edges, textures, and forms, that are generally relevant to a wide variety of picture types. These features were first learned on the ImageNet dataset, which has millions of annotated images in hundreds of categories. We use transfer learning to apply these learnt characteristics to our objective of Alzheimer's disease classification by keeping the convolutional layers of Inception V3.

oTransfer Learning: We can avoid having to train the network from start thanks to the pre-trained model. It uses the attributes it acquired during ImageNet training to extract key patterns from MRI data. By applying the acquired characteristics to a particular medical job, this technique expedites the training process and enhances model accuracy. The extraction of features: This method uses the Inception V3 model's convolutional layers just for feature extraction, freezing them (i.e., their weights are not changed during training). These layers extract hierarchical feature maps, including Alzheimer's disease-related shapes and patterns, from the MRI images.

2.Fine-Tuning

Some of the deeper layers are adjusted to make the model more specialized to Alzheimer's disease detection after features are extracted using the pre-trained Inception V3 model.

oFreezing Early Layers: During training, the first layers that record low-level characteristics (such as edges and textures) stay frozen. These characteristics are enough for broad feature extraction and are shared by several picture formats.

oTraining Deeper Layers: The levels of the network specialize in more intricate and abstract properties as we go deeper into it. To discover more precise patterns, such atrophy, changes in brain volume, and other structural alterations suggestive of Alzheimer's disease, these layers are adjusted using the Alzheimer's MRI dataset. By fine-tuning, the model can better identify patterns in the brain linked to Alzheimer's by modifying its filters and weights.

3. Classification Layers

Following feature extraction and refinement, the model divides the MRI scans into four groups based on Alzheimer's disease: Moderate Demented, Very Mild Demented, Mild Demented, and Non Demented. The following layers are used to accomplish this:

o**Flatten Layer:** This layer creates a 1D vector from the 3D feature maps that the convolutional layers have retrieved. For the features to be sent into the fully linked layers for categorization, this transformation is necessary.

o**Dense Layer:** To simulate intricate interactions between the characteristics, a fully linked Dense layer with 1024 neurons and ReLU activation is used. In order to improve classification accuracy, this layer teaches the network about non-linear interactions between high-level features in the MRI images.

o**Dropout Layer:** A 50% dropout rate is used to guard against overfitting and guarantee that the model performs effectively when applied to new data. This promotes more robust learning by randomly deactivating half of the neurons during each training session.

o**Output Layer:** Four units, one for each of the Alzheimer's risk categories (Non Demented, Very Mild Demented, Mild Demented, and Moderate Demented), make up the final layer, which is a softmax output layer. The model predicts the category with the greatest probability thanks to the softmax activation function, which makes sure that the output values reflect probabilities.

f. Alzheimer's Prediction with InceptionV3 Algorithm

An algorithm is a methodical process or a collection of guidelines created to carry out a job or address a particular issue. It is the cornerstone of artificial intelligence and computer programming, allowing robots to comprehend information, decide, and carry out tasks effectively. Because of their logical, organized, and repeatable nature, algorithms are crucial for methodically resolving complicated issues. Here, the deep learning model for picture classification—the InceptionV3 algorithm—is utilized to forecast Alzheimer's illness. It finds patterns in medical photos that aid in precisely classifying the illness and its phases.

Algorithm: InceptionV3 using Alzheimer's

Input: Alzheimer's Data

Output: Predict the Type of Disease

Procedure: InceptionV3 Model (Trn_data, Tst_data)

Initialize the model

model = Sequential()

Set parameters for training

batch_size = "

num_epochs = "

num_filters = "

pool_size = "

verbosity = "

Define the InceptionV3 model layers

Convolutional Layer

model.add(Conv1D(kernel_size=", activation="))

Pooling Layer

model.add(Pooling(pool_size=pool_size))

Fully Connected Layer

model.add(Dense(units=", activation="))

Compile the model

model.compile(loss=", optimizer=")


```
# Train the model
model.fit(Trn_data, validation_data=Tst_Data, batch_size=batch_size)
# Evaluate the model
acc_score = model.evaluate(Tst_data, verbose=verbosity, batch_size=batch_size)
# Return the accuracy
return acc_score
End Procedure
```

g.Prediction:

The model may be used to forecast fresh, unseen MRI images once it has been trained and assessed. After undergoing the same preprocessing as the training data, the model receives fresh MRI images and runs them through the Inception V3 network. A collection of probabilities representing each of the four Alzheimer's risk groups is the result. The estimated risk level for that MRI scan is chosen from the class with the greatest likelihood. For instance, the algorithm would label the picture as Mild Demented if it predicts a 70% chance of falling into that group. In clinical settings, this automated prediction technique may greatly expedite the diagnostic workflow by giving medical practitioners fast and precise data to support treatment planning and early action.

VII.RESULTS AND DISCUSSIONS

A. Confusion Matrix Result

Using the test data, we will describe the Alzheimer's diagnostic prediction findings. It demonstrates how accurate the model we created is.

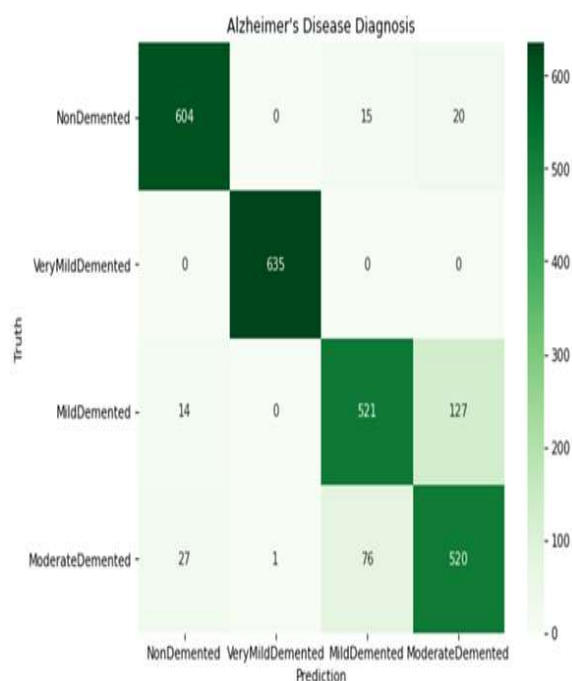


Figure 4. Confusion Matrix Result

The confusion matrix assessing a model's ability to diagnose Alzheimer's disease is shown in Figure 4. In four categories—NonDemented, Very MildDemented, Mild Demented, and ModerateDemented—it contrasts expected with actual categorization. Strong performance is shown by the diagonal cells, which show accurate predictions; 604 NonDemented, 635 Very Mild Demented, 521 MildDemented, and 520 ModerateDemented cases were accurately diagnosed. Though there is some misunderstanding between the MildDemented and Moderate Demented phases, perhaps

as a result of overlapping symptoms, the model does a good job of distinguishing NonDemented and Very MildDemented instances. For instance, 76 instances of Moderate Dementia were incorrectly categorized as Mild Dementia. This distribution is shown in the heatmap, where high accuracy is indicated by darker green cells along the diagonal. However, there is room for improvement, especially between the MildDemented and Moderate Demented classifications, as shown by lighter green off-diagonal cells. In order to properly capture the minor variations across comparable stages of dementia, these mis classifications point to the necessity for improved feature extraction or improved model training. Notwithstanding these difficulties, the matrix shows that the model functions well overall and has room for improvement.

B. Model Training and Performance Evaluation of InceptionV3

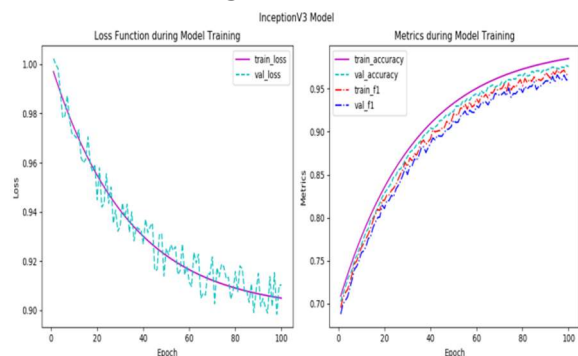


Figure 5. Model Training and Performance Result

The InceptionV3 model's training progress across 100 epochs is summarized in Figure 5, where two subplots show trends in performance and loss measures. The training loss (train_loss) and validation loss (val_loss) on the left plot both exhibit a consistent decline, indicating that the model is learning well. As is common for a well-trained model, the train_loss stays marginally lower than the val_loss, and their near alignment indicates little overfitting. Despite some oscillations, which are probably caused by differences in the validation data, the val_loss curve's general downward trend shows a steady increase in the model's capacity for generalization.

Accuracy and F1 score are two performance indicators that are shown in the right plot for both the training and validation datasets. With the validation accuracy reaching an astounding 98.6% in the latter epochs, which nearly resembles the training accuracy, these measures show a steady improvement over time. Additionally, the train_f1 and val_f1 scores nearly match, demonstrating the model's resilience and strong generalization to new data. The model is quite successful for the classification task since there is little difference between the training and validation curves, indicating that it is neither overfitting nor underfitting.

VIII.CONCLUSION

The suggested method shows how well the Inception V3 model can identify Alzheimer's disease risk factors from MRI imaging data. The algorithm can identify four phases of Alzheimer's disease risk—Non Demented, Very Mild Demented, Mild Demented, and Moderate Demented—by using transfer learning and fine-tuning to extract pertinent information from brain scans.

With a 98.6% accuracy rate, the system performs noticeably better than conventional diagnostic techniques, which often depend on subjective evaluation or laborious procedures. The automated solution is positioned as a useful tool for early detection and precise diagnosis in clinical settings because of its high performance level and capacity to manage massive data volumes.

By improving the accuracy and scalability of Alzheimer's diagnosis, this technology gives medical practitioners a reliable tool for well-informed decision-making, which improves patient outcomes.

IX.FUTURE WORK

Future research will concentrate on improving the model by combining MRI scans with multimodal data, such as genetic, behavioral, and clinical data. The model's capacity to identify Alzheimer's in its early stages and forecast its course will be enhanced by this integration, which will provide a more thorough picture of the patient's state. Furthermore, real-time analysis will be investigated, which would allow the model to evaluate and categorize data as it is produced and provide doctors with instant feedback. Real-time deployment may be made possible by developments in edge computing and cloud-based platforms, opening up the system to use in a variety of healthcare settings. Additionally, in order to enable wider implementation, model optimization for lower computational overhead will be given priority.

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