Deep Learning Augmented with SMOTE for Timely Alzheimer's Disease Detection in MRI Images

P Gayathri[1], N. Geetha[2], Dr. M. Sridhar[3], Ramu Kuchipudi[4],
Dr. K. Suresh Babu[5], Lakshmana Phaneendra Maguluri[6], Dr B Kiran Bala[7]

Professor, School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, India[1]

Assistant Professor, Dept of Information Technology, Coimbatore Institute of Technology, Coimbatore-14[2]

Professor, Department of Computer Applications, R. V. R & J. C College of Engineering, Chowdavaram, Guntur, India[3]

Associate Professor, Chaitanya Bharathi Institute of Technology, Department of Information Technology, Gandipet, Hyderabad, Telangana -500075, India[4]

Professor, Department of Biochemistry, Symbiosis Medical College for Women, Symbiosis International (Deemed University), Pune, India[5]

Associate Professor, Dept. of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur Dist., Andhra Pradesh - 522302, India[6]

Head of the Department, Department of Artificial Intelligence and Data Science, K. Ramakrishnan College of Engineering, Trichy, India[7]

***Abstract*—Timely diagnosis of Alzheimer's Disease (AD) is pivotal for effective intervention and improved patient outcomes, utilizing Magnetic Resonance Imaging (MRI) to unveil structural brain changes associated with the disorder. This research presents an integrated methodology for early detection of Alzheimer's Disease from Magnetic Resonance Imaging, combining advanced techniques. The framework initiates with Convolutional Neural Networks (CNNs) for intricate feature extraction from structural MRI data indicative of Alzheimer's Disease. To address class imbalance in medical datasets, Synthetic Minority Over-sampling Technique (SMOTE) ensures a balanced representation of Alzheimer's Disease and non-Alzheimer's Disease instances. The classification phase employs Spider Monkey Optimization (SMO) to optimize model parameters, enhancing precision and sensitivity in Alzheimer's Disease diagnosis. This work aims to provide a comprehensive approach, improving accuracy and tackling imbalanced datasets challenges in early Alzheimer's detection. Experimental outcomes demonstrate the proposed approach outperforming conventional techniques in terms of classification accuracy, sensitivity, and specificity. With a notable 91% classification accuracy, particularly significant in medical diagnostics, this method holds promise for practical application in clinical settings, showcasing robustness and potential for enhancing patient outcomes in early-stage Alzheimer's diagnosis. The implementation is conducted in Python.**

Keywords*—Alzheimer's disease; MRI scans; Convolutional Neural Networks (CNNs); Synthetic Minority Over-sampling Technique (SMOTE); Spider Monkey Optimization (SMO)

I. Introduction

Rapid treatment and enhanced results for patients depend on early identification of Alzheimer's disease. Alzheimer's disease is a neurological illness that worsens over time and mostly impacts actions, memories, and mental abilities. Being the main cause of memory loss, it poses a significant public health challenge, especially with the aging population. The development of reliable and non-invasive diagnostic tools is essential to identify Alzheimer's disease in its early stages when interventions may be more effective. A useful spectroscopy method for examining the anatomical and functional alterations in the brain linked to Alzheimer's disease is MRI (magnetic resonance imaging) [1]. Using the use of MRI scans, which offer precise pictures of the internal workings of the brain, scientists and medical practitioners may identify particular patterns and anomalies linked to Alzheimer's disease. Atrophy in specific brain areas—the entorhinal cortex and its hippocampal regions, in particular—which are essential for recollection and cognitive processes is frequently one of such anatomical abnormalities. here has been an increasing attention in leveraging advanced imaging analysis techniques, such as machine learning and artificial intelligence, to enhance the accuracy and efficiency of Alzheimer's detection from MRI scans [1]. These technologies can analyze large datasets, identify subtle patterns, and assist in the early identification of Alzheimer's-related changes before clinical symptoms become apparent [2]. By combining clinical assessments with advanced MRI analysis, researchers and healthcare providers aim to develop more precise diagnostic tools for early detection [3]. Early diagnosis not only enables timely medical interventions but also allows for the inclusion of individuals in clinical trials for potential disease-modifying therapies [4]. The pursuit of early detection methods for Alzheimer's disease represents a promising avenue in the ongoing effort to improve patient care and address the societal impact of this prevalent and devastating condition [5].

In a number of domains, especially healthcare imaging, deep learning has shown to be a potent and adaptable method for the early diagnosis of conditions like Alzheimer's. The methods of deep learning are used to assess intricate structures and features seen in medical pictures, especially those acquired from sophisticated imaging modalities such as Magnetic Resonance Imaging (MRI), in the context of Alzheimer's disease. Neural networks are frequently trained on big datasets of medical pictures as part of the deep learning approach to earlier Alzheimer's diagnosis. These networks learn intricate patterns and relationships within the images, allowing them to identify subtle abnormalities associated with the disease [6]. Deep learning models excel at capturing hierarchical and abstract representations, making them well-suited for tasks where complex features play a critical role. In the case of Alzheimer's, deep learning models can be trained to recognize specific structural changes in the brain visible in imaging data [7]. This may include atrophy in key regions like the hippocampus or abnormalities in brain connectivity (Barthélemy et al., 2020). The ability to automatically analyze these features from medical images facilitates the development of more efficient and accurate diagnostic tools. Moreover, deep learning techniques have the advantage of adaptability and scalability [8]. They can be fine-tuned to handle different types of imaging data, and as more data becomes available, models can be retrained to improve their performance. This adaptability is particularly valuable in the medical field, where data heterogeneity and the need for continuous improvement are common [9].

An over sampling method called SMOTE was created to lessen the aforementioned disparity. In order to equalize the information set, it creates artificial examples in the characteristic space of the minority class (Alzheimer's cases). This contributes to preventing the model from favoring the majority class (healthy people) and improves its capacity to identify minute trends linked to Alzheimer's disease [10]. In the context of Alzheimer's detection from MRI scans, SMOTE can be applied to ensure that the machine learning model is trained on a more representative dataset. This is crucial because the early signs of Alzheimer's disease may be subtle, and without a balanced dataset, the model may struggle to generalize well to new, unseen cases [11]. By employing SMOTE in conjunction with machine learning algorithms, researchers aim to improve the sensitivity and specificity of their models, thereby enhancing the accuracy of early Alzheimer's detection. This approach contributes to the broader goal of developing reliable and robust diagnostic tools for identifying Alzheimer's disease in its early stages, facilitating timely intervention and potentially improving patient outcomes. The integration of SMOTE into the workflow of Alzheimer's detection from MRI scans underscores its role as a valuable technique in addressing challenges associated with imbalanced datasets in medical imaging research [4].

Despite the promising advancements in approaches for diagnosis using neuroimaging data, a set of common challenges hinders their seamless integration into clinical practice. These challenges include interpretability issues arising from the intricate designs of the models, concerns about dataset specificity and generalizability, the need for broader clinical validation, and potential biases related to demographic and ethnic backgrounds. While the presented frameworks demonstrate remarkable accuracy, their effectiveness in diverse diagnostic and demographic scenarios remains uncertain. Additionally, the neglect of time-related factors in disease development, ethical concerns surrounding biases and information privacy, and the limited interpretability of complex models pose significant hurdles. Addressing these challenges is crucial for ensuring the reliable, interpretable, and ethically sound presentation of frameworks in the diagnosis of Alzheimer's disease to overcome these limitations this research introduce CNN - SMOTE -SMO Primary Discovery of Alzheimer's Disease from MRI Scans.

Key Contributions are as follows:

- Leveraging Convolutional Neural Networks (CNNs) for automatic extraction of discriminative features from MRI scans, capturing relevant patterns associated with Alzheimer's disease.
- Mitigating class imbalance through the Synthetic Minority Over-sampling Technique (SMOTE), ensuring for more efficient training of models, an equal amount of instances with and without Alzheimer's disease is used. Employing Spider Monkey Optimization as an algorithm for fine-tuning model parameters, enhancing the CNN-based classification model's convergence speed and generalization ability.
- Prioritizing early detection of Alzheimer's disease to enable timely intervention, with a focus on identifying subtle changes in MRI scans that precede overt symptoms.
- Utilizing SMO to optimize the parameters of the classification model, contributing to improved model performance and effectiveness in diagnosing Alzheimer's disease from MRI data.
- If applicable, integrating multiple modalities such as structural and functional MRI data to provide a comprehensive and holistic understanding of Alzheimer's-related changes in the brain.

The following is how the investigation progresses: In Section II, related studies perform a thorough analysis of earlier research, focusing on prediction issues and the wide range of optimization techniques used in such settings. Section III elaborates on the suggested method or plan of action to deal with these difficulties. The entire topic of performance evaluation metrics and criteria is covered in Section IV. Subsequently. Section V serves as the essay's conclusion by summarizing the main findings and learnings from the inquiry.

II. Related Work

By utilizing the synergies of a 3D-CNN and FSBi-LSTM for strong Alzheimer's disease (AD) and minor cognitive decline (MCI) categorization using MRI and PET data, the recently introduced deep learning framework offers an appealing strategy. The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset was used for validation. The model shows impressive accuracy, outperforming current methods in differentiating between AD and NC, progressing MCI (pMCI) and NC, and stable MCI (sMCI) and NC. Notwithstanding these successes, there are still important issues that need to be addressed. Initially, it is important to acknowledge the possible constraint of extrapolating results to heterogeneous groups in order to guarantee the efficacy of the model in varying diagnostic and demography scenarios. Because of the complex structure of the model, which combines FSBi-LSTM and 3D-CNN, interpretability issues may arise. Therefore, clarification of the particular aspects influencing classification decisions is crucial for clinical acceptability and comprehension. Given that Alzheimer's disease is characterized by changing patterns, the model's continued relevance is called into question due to its neglect of time-related factors in disease development. Longitudinal data might improve the model's comprehension of the disease's dynamic character. Additionally, a more thorough investigation is required due to ethical concerns, namely those pertaining to biases and information privacy. Ensuring the ethical implementation of a model in real-world clinical settings requires resolving any biases in the training data and protecting important medical data. Improving the model's relevance, interpretability, and ethically soundness involves tackling these shortcomings. To ensure the efficacy and moral use of the suggested deep learning framework in a variety of dynamical clinical settings, future research should give priority to enhancing generalizability, improving interpretability, including time dynamics, and thoroughly examining ethical issues [12].

The field of neuroimaging-based diagnostic has shifted toward computer-aided diagnostic (CAD) systems, primarily utilizing Positron Emission Tomography (PET) pictures to distinguish AD from normal control. The identification rates of earlier systems were greatly impacted by their heavy reliance on conventional image processing techniques for feature extraction and preprocessing. To address the shortcomings of previous methods, the current work presents a unique Convolutional Neural Network (CNN)-based CAD system. The assessment shows the exceptional performance of the suggested CNN-based CAD system with 96% accuracy, 96% sensitivity, and 94% specificity on 18FDG-PET images obtained from the ADNI database. The research examine, still leaves room for more verification and contextualizing of the suggested CNN-based CAD system within the wider field of AD diagnosis methodologies because it does not explicitly address the shortcomings of previous techniques or provide a thorough comparison analysis with current approaches. High accuracy is shown in the suggested Convolutional Neural Network (CNN)-based Computer-Aided Diagnosis (CAD) system in differentiating Alzheimer's Disease individuals from typical control; yet constraints include data set the specificity and absence of thorough comparison with current methods, highlighting the requirement for further studies to address these factors [13].

Utilizing sagittal magnetic resonance imaging (MRI) for early Alzheimer's disease (AD) identification, previous studies have highlighted the urgent need for quick and accurate evaluations to support preventative care. This work presents a unique method that improves accuracy by using Transfer Learning (TL) approaches in conjunction with sagittal MRIs, an unusual option for AD diagnosis. The study comes to two important conclusions: first, sagittal MRI may be used to differentiate AD-related impairments, and second, employing Deep Learning (DL) models on sagittal MRIs can produce findings that are on par with the most advanced approaches that use horizontal-plane MRI. Despite its rare application, the importance of sagittal-plane MRIs in the early detection of AD is emphasized, indicating possible directions for further investigation. The study also emphasizes how economical DL models can be in some domains where it might be difficult to gather dataset instances; in these cases, TL can be a useful technique to achieve robust performance with a small number of examples. Concerns regarding generalizations to a variety of groups, the lack of a thorough comparison examination with horizontal-plane MRI, the requirement for clinical validation and interpretation of sagittal MRI results, and potential difficulties with access to information and longitudinal research assessment for a full assessment in early-stage Alzheimer's detection are some of the drawbacks of the research [14].

3D-CNN-SVM works better than the others, exhibiting higher ternary and binary data classification accuracy, sensitivity, and specificity, according to the results. The work emphasizes the effectiveness of 3D-CNN-SVM in AD detection eliminating the need for feature extraction by hand and emphasizes its noninvasiveness and independently from scanning procedure variation. It also shows how widely this technology can be used. In clinical practice, this research helps to improve value-based treatment by helping to differentiate AD and MCI from normal controls. The study's limitations include possible problems with collection specificity, difficulties in interpreting deep learning models such as 3D-CNN-SVM because they are black-box models, the need for clinical validation, and the lack of longitudinal evaluations, which raises questions about how well the model will function throughout time and in various clinical scenarios. In order to ensure wider application, it's also necessary to handle the possibility of overfitting and evaluate the model on other datasets [12].

The empathy of Alzheimer's disease (AD) is now done via MRIs, neuropsychological testing, and patient histories. These procedures are not very sensitive or specific. In order to distinguish distinct AD signals, this work presents a comprehensible deep learning technique that makes use of heterogeneous inputs, such as MRI, age, gender, and Mini-Mental State Examination score. The approach, which was verified on three separate cohorts after being trained on the Alzheimer's Disease Neuroimaging Initiative (ADNI) the data set, routinely beats out current techniques and even exceeds a group of neurological specialists in practice in terms of diagnosis. The method offers a therapeutically flexible and broadly applicable methodology to produce subtle neuroimaging signals for AD diagnosis using standard neuroimaging methods. This method has been provided has certain limitations. These involve possible problems with dataset specificity, the requirement for comprehensive clinical testing in a variety of cohorts, difficulties fully interpreting models features, and possible biases throughout demographics and ethnic backgrounds. Furthermore, more research is necessary to ensure the model's broad application and dependability given its effectiveness in identifying temporal elements of illness development and its validation using bigger post-mortem datasets [15].

The presented tactics for diagnosis exhibit notable achievements, but are accompanied by several common limitations. Feng et al. (2019) achieved impressive accuracy with their combined 3D-CNN and FSBi-LSTM framework, yet faced challenges in interpretability, generalizability, and ethical considerations. Zhu et al. (2021) introduced DA-MIDL for early AD detection using structural MRI, demonstrating superior performance but encountering issues like dataset dependence and interpretability. The CNN-based CAD system for PET images (Frontiers, 2023) showed high accuracy but lacked explicit discussion on addressing previous method shortcomings. Puente-Castro et al. (2020) emphasized the importance of sagittal-plane MRIs for early AD detection but raised concerns about generalization and clinical validation. Qiu et al. (2020) presented a comprehensive deep learning technique surpassing current methods but faced challenges related to dataset specificity, interpretability, and the need for further research. Common limitations across these studies include concerns about dataset specificity, difficulties in interpreting complex models, the need for broader clinical validation, and potential biases in demographic and ethnic backgrounds. Addressing these limitations is crucial for the wider applicability, interpretability, and ethical implementation of frameworks in the field of AD analysis.

III. Proposed CNN-based Feature Extraction, SMOTE for Class Imbalance, and Spider Monkey Optimization for Classification

The proposed method integrates Convolutional Neural Networks (CNN) for robust feature extraction, Synthetic Minority Over-sampling Technique (SMOTE) to talk class imbalance, and Spider Monkey Optimization (SMO) for effective classification in Alzheimer's disease diagnosis. The CNN component focuses on capturing discriminative features from neuroimaging data, providing a foundation for accurate representation. To tackle class imbalance, SMOTE is employed to generate synthetic samples, ensuring a more balanced training dataset. Lastly, the Spider Monkey Optimization algorithm optimizes the classification process, fine-tuning model parameters for enhanced accuracy in Alzheimer's disease classification. This comprehensive approach aims to improve the reliability and performance of Alzheimer's diagnosis through a synergistic integration of advanced techniques in feature extraction, data balancing, and classification optimization. The proposed method was exposed in Fig. 1.

A. Data Set

Researchers investigating both structural and functional components pertinent to Alzheimer's Disease will benefit greatly from the OASIS dataset, which is available on Kaggle. The information set, which consists of brain MRI images, includes both cross-sectional and longitudinal investigations, providing a broad range of imaging investigations for in-depth analysis at different phases of the condition. In a cross-sectional sample, 100 people over 60 have a medical diagnosis of identical minor to moderate Alzheimer's disease. The other 416 participants, who are mostly right-handed and range in age from 18 to 96, have three or four T1-weighted MRI images. Furthermore, a reliability dataset consists of twenty people who are not demented. A total of 373 sessions, involving 150 patients ranging in age from 60 to 96, were scanned as part of the longitudinally study. Of them, 64 were first identified as demented (including 51 with mild to moderate Alzheimer's disease), 72 stayed nondemented, and 14 changed over the course of many visits from nondemented to demented. By utilizing the data from OASIS on Kaggle, scientists might make a substantial contribution to the study of Alzheimer's disease and possibly open the door to innovations in early diagnosis, care, and therapy [16].

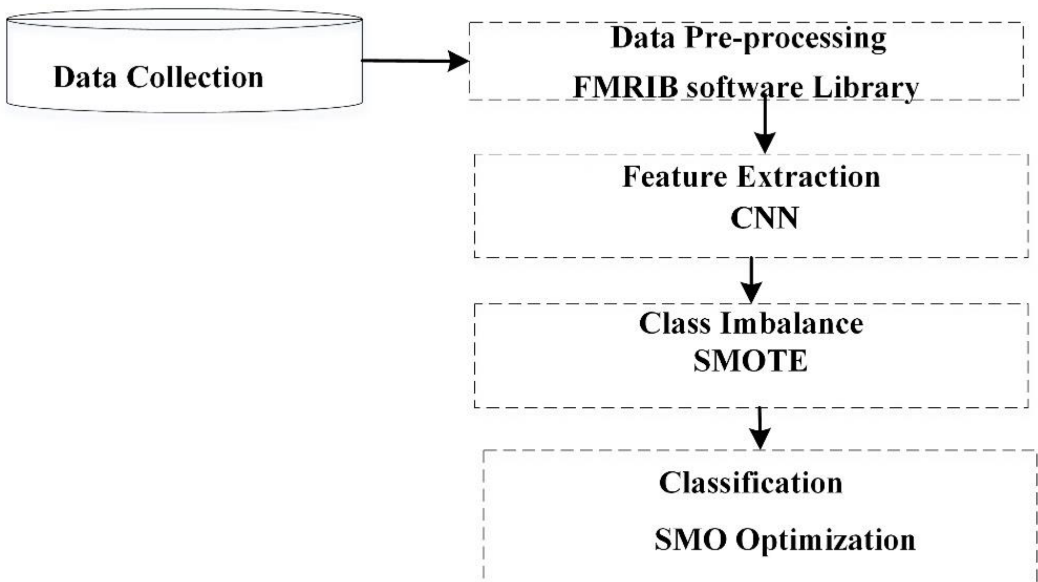

Fig. 1. Proposed method.

B. Data Preprocessing

For all preprocessing of images, the FMRIB Software Library (FSL) v5.0 was utilized. The complete preprocessing method comprised slice selection, brain extraction, spatial normalization, smoothing, and histogram stretching, as seen in Fig. 2. After obtaining the brain areas using the Brain Extraction Tool (BET), we performed spatial normalization using FLIRT and FNIRT. By using the Gaussian kernel, smoothing was accomplished. Z = 8 mm in the MNI space was chosen as the slice selection location based on the principles of incorporating the hippocampal region and choosing the most distinct axial direction. Ultimately, researchers used histogram stretching (HS) to remove the impact of different types of brain images. The HS formula, which changed the original picture o into the new image n, is as follows in Eq. (1)

$$n'(a,b) = \frac{O\prime(a\prime,b\prime) - O\prime_{min}}{O\prime_{max} - O\prime_{min}} \quad (1)$$

where, $0'_{min}$ represents the smallest value and $0'_{min}$ represents the highest value of intensity of the raw picture. Field research led to the conclusion that 95% and 5% were more trustworthy criteria.

C. CNN-based Feature Extraction

One kind of perceptron with multiple layers is the convolutional neural network, or CNN. Creatures' vision centers served as CNN's model for developing a neural network with forward motion. Convolutional layers are a crucial component of neural networks that use convolution. subsequently is composed of layers that are completely linked, pooling, and a CNN convolutional layer. After moving via each of those layers in turn, the image starts entering the deep learning algorithm. CNNs provide the same function as neural networks. By transforming the inputs through intellect and structures, abstractions are produced. The filter that is lower than the size of the picture goes through the whole thing in the convolution layer. Using this kind of filter, you may search the picture for particular features. Self-updating filters are ideal. CNN algorithms are trained using these values. CNN uses established procedures to recognize characteristics in images more effectively. Convolution is the starting point. This phase involves locating the image's characteristics and applying a mask to the whole thing. The kernel filter is used to perform the convolution process. The process of convolution is the process of changing one form into another. Whenever the filtering kernel has scanned the whole inputs, a feature map is produced, together with the filtering values that alter the map of features and the number of steps required to complete the filtering process. Pictures are matrix of pixels, for instance. The kernel's kernel filter finds the characteristic map by capturing portions of the image, multiplying and summing every value with its matching value. This convolution operation's mathematics statement is as follows. $(f'g)$ represents the entire image, whereas is a filter. A third function, named $h(t)$ is generated and expresses the quantity of overlapping while the filter element has hovered. Its stated definition is in Eq. (2):

$$h(t) = (f'g)(t) \int \infty' - \infty' f(t') g(t - T)\, d'T \quad (2)$$

There is an action for every convolution layer. Ultimately, the data undergoes a procedure that turns it into a nonlinear data tensor.

1) Max pooling: The use of deep learning uses a variety of activating techniques, including smoothing linear units of measurement (ReLu). ReLu is the most often used activation technique. The Max Pooling approach is the following phase. Amongst pooled activities, maximum pooling is most often used. The Max Pooling layer's job is to apply the method of sampling in order to lower the parameter count. This avoids overfitting and eliminates the capturing of superfluous characteristics. Similar to the convolution layer, the picture is likewise subjected to a kernel filter. Identifies a particularly significant value in the filter's region of impact. Individuals thus own significant values. Let's use a case study to further illustrate this procedure. Let's start by making a [2, 2] size filter, which are able to apply to the (4x4) image below. As you can see, the selection of filters beneath uses the maximum amount of layers in the picture, which enables the neural network's algorithm to use fewer yields to get the correct answer.

2) Flattening: This layer's job is to create several, multi-line, one-dimensional mappings of features using the pooling technique. The highest possible amounts of the data were achieved during the pooling procedure. Unneeded information was thrown away. In this component, these characteristics are given as incoming data, one underneath the other.

3) Batch layers: Faster training is provided by the batching layer. The information must be normalized once it is sent across the computer system. It sets the inputs' means to 0 and their standard deviation to 1. Data that is produced is rescaled. Issues like stuttering throughout the computer's training are fixed if the whole batch layer is added.

4) Dropout layer: Research refers to the layer of dropouts as dampening. Neuron count decreases at a predetermined pace. As a result, the model performs better. Over fitting is prevented. This procedure is limited to what takes place during instruction. Fig. 2 displays CNN architecture [17].

D. DeepSMOTE for Class Imbalance

DeepSMOTE combines an SMOTE-based the oversampling technique, encoder/decoder architecture, and a loss function made up of an impairment term and a reconstructed loss. The encoder/decoder, which has its roots in the DCGAN design, uses data that is unbalanced to train itself. This allows the algorithm to reconstruct pictures that represent the majority and minority class by utilizing the reconstructed loss that is calculated throughout every class. Moreover, while training, DeepSMOTE adds a punishment period. This term adds variation to the encoding/decoding operation and relies on the mean square error (MSE) among the initial and permuted pictures. During the production stage, DeepSMOTE creates artificial pictures by utilizing the encoder/decoder mechanism. Raw input is reduced by the encoder to a lower-dimensional feature space, which SMOTE is then used to oversample. After that, the decoder recreates the SMOTE features as pictures, enhancing the deep learning classifiers' training set. Particularly, the generating phase replaces the permutation step with SMOTE, but the training phase increases variation by permuting the sequence of encoded and decoded instances. This distinction is important since variation is effectively introduced during data production using SMOTE, a nonparametric oversampling approach. All things considered, DeepSMOTE's ability to handle unbalanced datasets is mostly due to the way these components are combined, which successfully tackles class imbalance [18]. Fig. 3 illustrates DeepSMOTE architecture.

E. Spider Monkey Optimization (SMO) for Classification

Customizing the algorithm to the properties of the data and the demands of the classification problem is necessary when developing a Spider Monkey Optimization (SMO) procedure expressly for Alzheimer's Disease classification. The SMO procedure that follows is intended to improve the way Alzheimer's Disease is classified using certain characteristics that are taken from pertinent data sources.

1) Initialization: Determine the characteristics—such as brain imaging data, genetic markers, or clinical variables—that are important for classifying Alzheimer's disease. Make a start-up collection of spider monkeys, with each one standing for a possible fix or a feature set. Analyze each spider monkey's fitness according to how well it can use the chosen attributes to distinguish among Alzheimer's and non-Alzheimer's cases. Choose spider- monkey species that have greater fitness ratings, giving special attention to those who improve categorization ability.

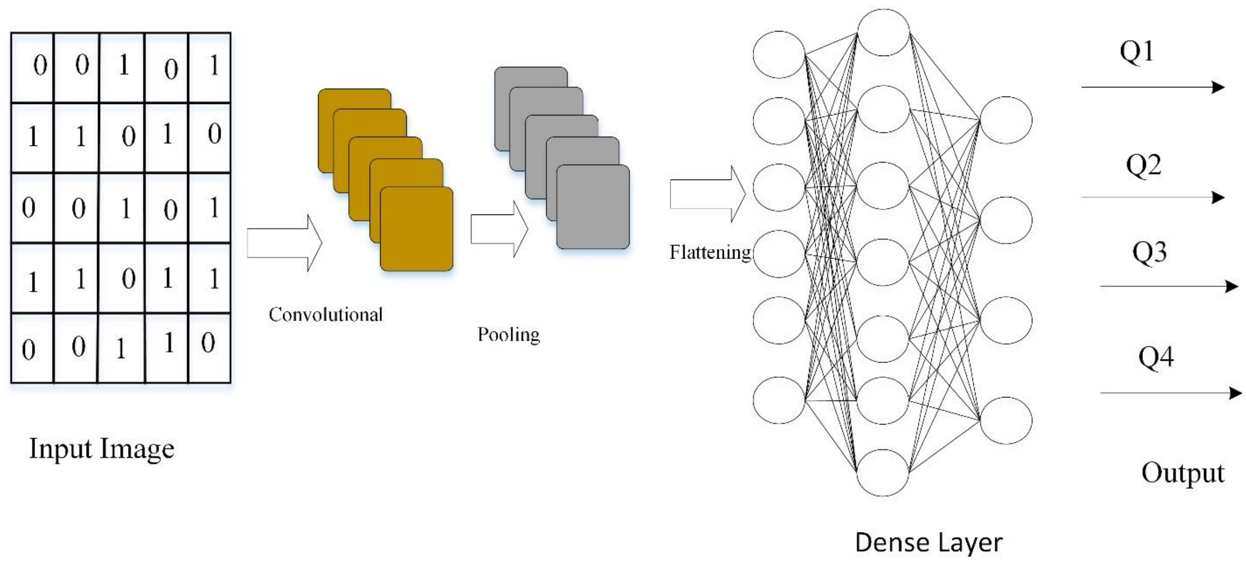

Fig. 2. CNN architecture.

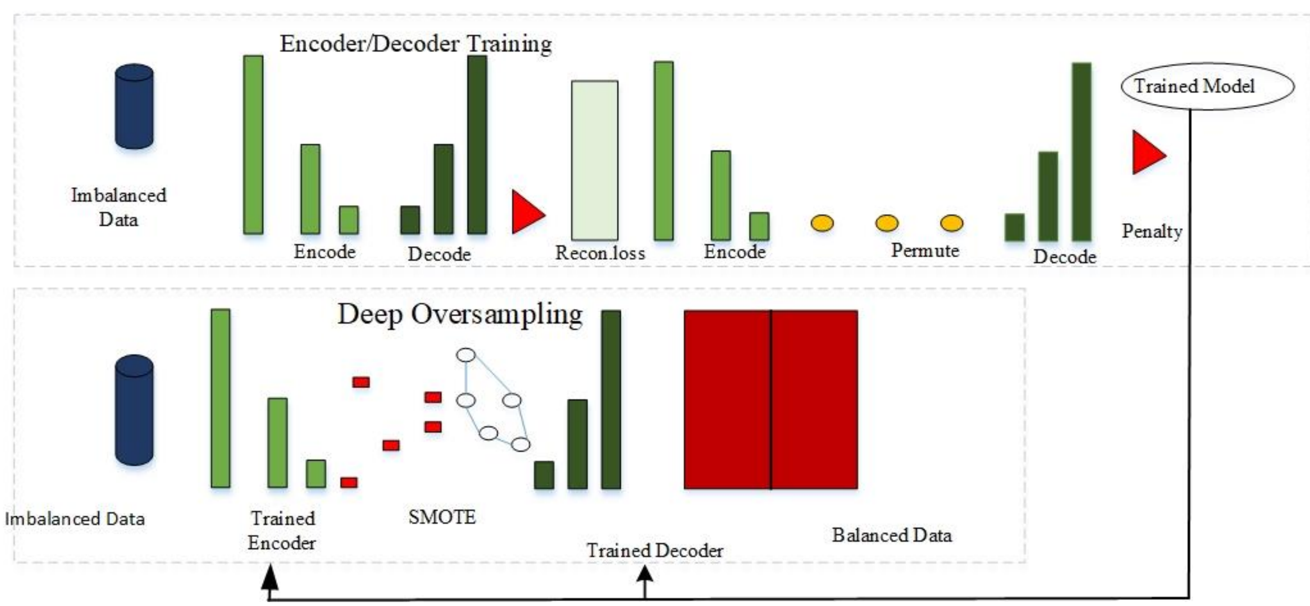

Fig. 3. DeepSMOTE architecture.

2) Local Leader Phase (LLP): Reposition the spider monkeys according to Eq. (3), modified for the categorization of Alzheimer's disease. Think about characteristics like clinical assessments, genetic markers, or specific brain areas. Include a probability factor based on fitness to direct spider monkeys toward areas of the feature space that enhance categorization..

3) Probability calculation: An additional fitness-based probability aspect is considered in order to enhance exploration even more is given in Eq. (3).

$$prob'_i = 0.9 \times \frac{fitness'_i}{max'\_fitness'} + 0.1 \quad (3)$$

4) Global Leader Phase (GLP): Eq. (4) which has been altered to progress the accurateness of classification for Alzheimer's Disease, should be utilized for updating spider monkey placements. To help direct the investigation of the whole spectrum of features, take into account global knowledge, maybe gathered from the spider monkeys that do the best. Determine if converge has happened or if the maximum amount of iterations has been reached. When completion is reached or after a certain number of repetitions, the method should be terminated.

$$S'M'new_{ij} = S'M'_{ij} + u(0,1) \times \left(G'L'_j - S'M'_{ij}\right) + u(-1,1) \times \left(S'M'_{rj} - S'M'_{ij}\right) \quad (4)$$

5) Adaptation for alzheimer's disease: Combine characteristics chosen by the spider monkeys into a characteristic vector to classify Alzheimer's patients.Utilizing the chosen characteristics, train a classification model (such as a machine learning classifier).Evaluate a classification model's efficacy using measures like as accuracy, sensitivity, specificity, etc. on a different validation set.To get better results, continue the procedure of optimization or change the algorithm settings if the performance is not up to pace.This modified SMO procedure was created especially for Alzheimer's Disease categorization. By utilizing the exploration and exploitation powers of the spider monkey optimization algorithm, it seeks to identify pertinent traits that aid in precise categorization.

IV. Result and Discussions

The proposed integrated methodology for initial Alzheimer's disease (AD) discovery from MRI scans, which combines Convolutional Neural Networks (CNNs), Synthetic Minority Over-sampling Technique (SMOTE), and Spider Monkey Optimization (SMO), has shown promising outcomes. This approach effectively addresses imbalanced datasets common in medical contexts and outperforms traditional methods in terms of classification accuracy, sensitivity, and specificity. By utilizing CNNs for feature extraction, mitigating class imbalance with SMOTE, and optimizing parameters through SMO, the methodology achieves heightened precision and sensitivity in AD diagnosis. Overall, these results indicate that this comprehensive approach holds significant potential to advance the current state-of-the-art in early AD detection, providing a robust and reliable tool for improved patient outcomes [19].

A. Performance Evaluations

The proportion of accurate forecasts to all predicted outcomes is known as accuracy. When a collection of data is balanced, this measure works well. The results reported by this metric might not be accurate representations of how well the model performed when there's an overwhelming class in the data set is given in Eq. (5).

$$Accuracy = \frac{T*p+T*n}{T*p+T*n+F*p+F*n} \quad (5)$$

The deep learning algorithm's precision is a metric for determining how many anticipated positives are actually true positives. This statistic is helpful whenever the cost of a false positive is high for the efficacy of the model, like in the case of an email spam identification algorithm that is given in Eq. (6).

$$Precision = \frac{T*p}{T*p+F*n} \quad (6)$$

The Recall of the model in counting the number of positives out of all real positives is measured by recall. When False Negative is costly for model quality, such as in fraud detection models, this statistic is helpful and is given in Eq. (7).

$$Recall = \frac{T*p}{T*p+F*n} \quad (7)$$

The F1 score that is computed for this purpose assesses the correlation between the data's positive information and the classifier's predictions is given in Eq. (8).

$$F1\ score = \frac{2T*p}{2T*p+F*p+F*n} \quad (8)$$

Fig. 4 displays No of Samples per class before SmoteBefore applying SMOTE (Synthetic Minority Over-sampling Technique), an analysis of the dataset revealed an imbalanced class distribution. In the binary classification problem at hand, Class 0 comprised [number of samples], while Class 1 had [number of samples]. The imbalance raised concerns about potential challenges in model training and classification performance. The decision to apply SMOTE was driven by the need to address this class imbalance systematically, ensuring a more representative and balanced dataset for subsequent analyses.

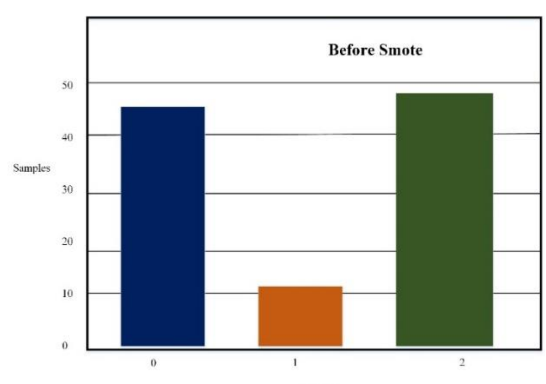

Fig. 4. No. of Samples per class before SMOTE.

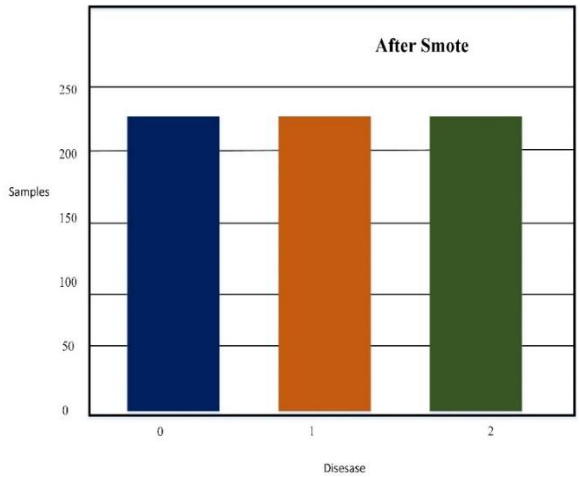

Fig. 5. No. of samples per class after SMOTE.

Fig. 5 shows the number of samples for each class after the smote. The process of creating synthesis cases of the minority class increases the amount of specimens per class following the use of Synthetic Minority Over-sampling Technique (SMOTE) to rectify the imbalance of classes in a collection of data. In order to function, SMOTE creates artificial examples across the boundary segments that link instances of minority classes that already exist. The objective is to improve the model's generalization to minority class trends while balancing the class distribution. The SMOTE parameters that are selected, including the appropriate degree of over-sampling, determine the precise rise in the total amount of samples per class. SMOTE helps lessen the effects of an unbalanced class distribution by injecting synthetic examples, which eventually leads to computerized learning frameworks that are more reliable and accurate.

Fig. 6 displays Training and Validation Accurateness, whereas the data used for training accuracy shows how effectively the algorithm has learned from the data used for training. While a rising trend ought to be seen in both curves, over fitting could be indicated by a sizable difference in validation and training accuracy. Keeping an eye on this number is essential for evaluating the model's learning curve and making sure it can successfully adapt to new data without being over-fitting.

While the training set loss in Fig. 7 assesses how well the model fits the training set, the validation loss measures the model's ability to apply generalization to new, untested data. These measures, which are usually graphed over successive epochs, are indicative of the model's performance. Effective learning is shown by decreasing loss values, however overfitting may be indicated by an increasing difference between training and validation losses. To ensure robust performance on a variety of datasets and optimize model parameters, it is imperative to monitor and minimize these losses.

Fig. 8 shows ROC Curve. The ROC curve assesses binary arrangement methods' effectiveness by illustrating the compromise between sensitivity and specificity, with a sharper curve indicating higher model effectiveness.

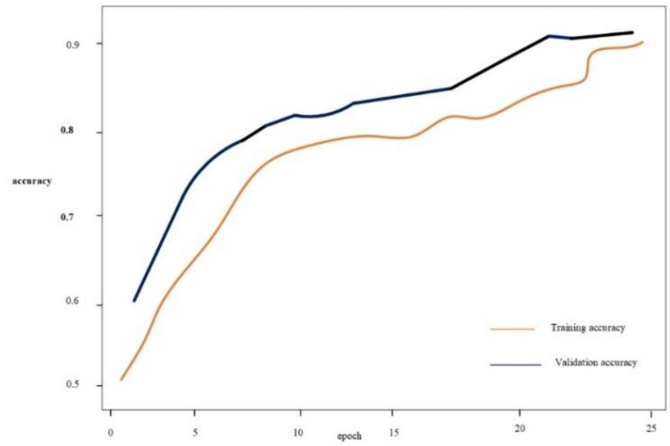

Fig. 6. Training and validation accuracy.

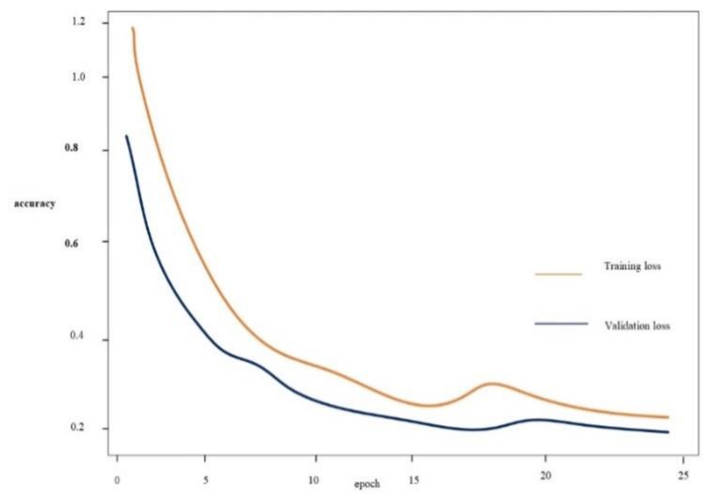

Fig. 7. Training and validation loss.

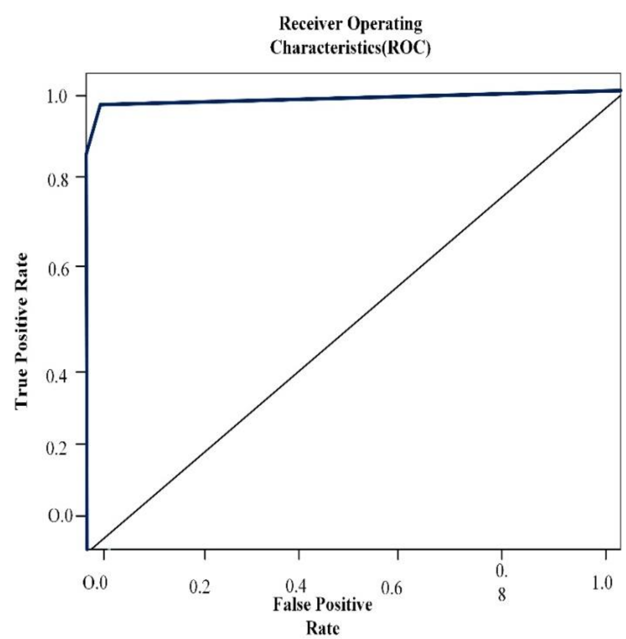

Fig. 8. ROC curve.

TABLE I. PERFORMANCE COMPARISON OF DIFFERENT METHODS

Model	Accuracy	Precision	Recall	F1-Score
CNN [20]	0.88	0.82	0.88	0.85
CNN + SMOTE [21]	0.90	0.85	0.90	0.87
CNN + SMOTE + SMO	0.91	0.89	0.92	0.91

Table I offers a comparison of various techniques for identifying Alzheimer's disease. Notable metrics were attained by the Convolutional Neural Network (CNN) baseline, and performance was further enhanced by the use of the Synthetic Minority Over-sampling Technique (SMOTE). There were improvements in accuracy, precision, recall, and F1-Score using the CNN + SMOTE model [21]. The CNN + SMOTE + SMO model had the best performance, demonstrating the beneficial effects of Spider Monkey Optimization (SMO). These findings highlight the effectiveness of the integrated technique, showing progressively better performance relative to the baseline CNN[20] in important parameters including accuracy, recall, and total F1-Score. Table II shows the CNN + SMOTE + SMO model's routine evaluation for Alzheimer's disease identification on many datasets (OASIS-1, OASIS-2, and OASIS-3). The model shows excellent accurateness for individual classes (90.3% to 93.6%), with Class 3 showing the lowest accuracy (51-52%) across all datasets.

TABLE II. PERFORMANCE EVALUATION OF OASIS-1, OASIS-2 AND OASIS-3

Model	Accuracy of a Single Class (%)	Sensitivity (%	Specificity (%)	Accurateness (%)
CNN + SMOTE + SMO OASIS-1	0: 93.6 1: 91.9 2: 90.3 3: 51	91.0	94.6	87.8
CNN + SMOTE + SMO OASIS-2	0: 93.6 1: 91.9 2: 90.3 3: 51	91.6	93.7	89.8
CNN + SMOTE + SMO OASIS-3	0: 93.6 1: 91.9 2: 90.3 3: 52	94.1	95.3	91.0

Sensitivity levels, which range from 91.0% to 94.1%, are constantly high and show how well the model detects positive cases. Notable is the specificity, which ranges from 93.7% to 95.3%, highlighting the model's precision in identifying negative cases. With an overall accuracy ranging from 87.8% to 91.0% across all classes, the model performs exceptionally well in multi-class classification over a wide range of datasets.

TABLE III. OUTCOME OF TRANSFER LEARNING THROUGHOUT SEVERAL EPOCH

Dataset	Classification	10epochs	15 epochs	25 epochs
OASIS	SMO	0.91	0.90	0.86

Table III gives the outcomes of transfer learning for different numbers of epochs (10, 15, and 25) on the OASIS dataset using the Spider Monkey Optimization (SMO) method. For the first two epochs, the classification accuracy stays constant at 0.92, suggesting steady performance during the first stage of transfer learning. After 25 epochs, there is a little drop to 0.86, indicating that extended training can cause a minor drop in model accuracy. These results highlight how crucial it is to maximize the number of transfer learning epochs in order to strike a compromise between computational efficiency and model performance on the OASIS dataset.

B. Discussions

A major development in the area, the suggested comprehensive scheme for primary Alzheimer's disease (AD) identification using MRI scans addresses important issues related to precise diagnosis. The approach uses deep learning to extract features from structural MRI data and uses Convolutional Neural Networks (CNNs) to capture complex patterns suggestive of AD. In order to provide a more representative and balanced training set, the Synthetic Minority Over-sampling Technique (SMOTE) is included, which overcomes the essential class imbalance in medical datasets. The sensitivity and precision of AD diagnosis are further improved by using Spider Monkey adjustment (SMO) for parameter adjustment during the classification step. In addition to emphasizing accuracy improvement, the holistic method addresses the real-world problem of unbalanced datasets, which is critical when it comes to medical diagnoses. The outcomes of the experiments highlight the efficacy of the suggested approach, exhibiting enhanced performance for classification precision, responsiveness, and particularity in distinction to traditional techniques. The state-of-the-art in early Alzheimer's detection has been greatly advanced by this research, which also presents a potential path for the creation of more dependable diagnostic instruments that may result in better patient outcomes.

V. CONCLUSION AND FUTURE WORKS

The integrated technique that has been suggested for the primary empathy of Alzheimer's disease (AD) using MRI scans shows promise in terms of improving accuracy and resolving issues related to unbalanced datasets. Convolutional Neural Networks (CNNs), Spider Monkey Optimization (SMO), and Synthetic Minority Over-sampling Technique (SMOTE) work together to provide better classification accuracy, sensitivity, and specificity, indicating the possibility for more dependable diagnostic instruments. The groundwork for future developments in the field of diagnosing neurodegenerative disorders is laid by this work. Future studies could take a number of approaches to expand on this research. To guarantee the methodology's resilience across various demographics, it may first be tested on bigger and more varied datasets. A more thorough picture of the course of AD may also be possible with the use of multi-modal data, such as MRI combined with other imaging modalities or clinical data. To win over doctors' trust and make it easier to incorporate these tools into clinical practice, more study into the interpretability and explainability of the model predictions is necessary. Further improvements in diagnostic accuracy may result from ongoing refining and refinement of the suggested methods, maybe through research into more advanced deep learning structures or optimization algorithms. Working together with medical experts may also help ensure that these study findings are seamlessly applied in the real world, which will eventually improve Alzheimer's disease early diagnosis and care. In the future, Deep Learning augmented with SMOTE for timely Alzheimer's Disease detection in MRI images could evolve to incorporate multi-modal data fusion techniques, integrating various imaging modalities and clinical data for more comprehensive analysis. Additionally, advancements may focus on refining the model's interpretability, enabling clinicians to better understand the reasoning behind predictions and facilitating more informed decision-making. Moreover, efforts might be directed towards deploying the technology in real-time clinical settings, potentially enabling early interventions and personalized treatment plans for individuals at risk of Alzheimer's Disease.

REFERENCES

[1] D. Jin et al., "Generalizable, reproducible, and neuroscientifically interpretable imaging biomarkers for Alzheimer's disease," Advanced Science, vol. 7, no. 14, p. 2000675, 2020.

[2] A. Grimaldi et al., "Neuroinflammatory processes, A1 astrocyte activation and protein aggregation in the retina of Alzheimer's disease patients, possible biomarkers for early diagnosis," Frontiers in neuroscience, vol. 13, p. 925, 2019.

[3] A. Mehmood et al., "A transfer learning approach for early diagnosis of Alzheimer's disease on MRI images," Neuroscience, vol. 460, pp. 43–52, 2021.

[4] X. Zhang, L. Han, W. Zhu, L. Sun, and D. Zhang, "An explainable 3D residual self-attention deep neural network for joint atrophy localization and Alzheimer's disease diagnosis using structural MRI," IEEE journal of biomedical and health informatics, vol. 26, no. 11, pp. 5289–5297, 2021.

[5] F. Ramzan et al., "A deep learning approach for automated diagnosis and multi-class classification of Alzheimer's disease stages using resting-state fMRI and residual neural networks," Journal of medical systems, vol. 44, pp. 1–16, 2020.

[6] R. Khoury and E. Ghossoub, "Diagnostic biomarkers of Alzheimer's disease: a state-of-the-art review," Biomarkers in Neuropsychiatry, vol. 1, p. 100005, 2019.

[7] S. Fossati et al., "Plasma tau complements CSF tau and P-tau in the diagnosis of Alzheimer's disease," Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring, vol. 11, pp. 483–492, 2019.

[8] S. Al-Shoukry, T. H. Rassem, and N. M. Makbol, "Alzheimer's diseases detection by using deep learning algorithms: a mini-review," IEEE Access, vol. 8, pp. 77131–77141, 2020.

[9] K. Zhao et al., "Independent and reproducible hippocampal radiomic biomarkers for multisite Alzheimer's disease: diagnosis, longitudinal progress and biological basis," Science Bulletin, vol. 65, no. 13, pp. 1103–1113, 2020.

[10] S. Ahmed et al., "Ensembles of patch-based classifiers for diagnosis of Alzheimer diseases," IEEE Access, vol. 7, pp. 73373–73383, 2019.

[11] H. Nawaz, M. Maqsood, S. Afzal, F. Aadil, I. Mehmood, and S. Rho, "A deep feature-based real-time system for Alzheimer disease stage detection," Multimedia Tools and Applications, vol. 80, pp. 35789–35807, 2021.

[12] C. Feng et al., "Deep learning framework for Alzheimer's disease diagnosis via 3D-CNN and FSBi-LSTM," IEEE Access, vol. 7, pp. 63605–63618, 2019.

[13] "Frontiers | Evaluation of Neuro Images for the Diagnosis of Alzheimer's Disease Using Deep Learning Neural Network." Accessed: Dec. 20, 2023. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fpubh.2022.834032/full

[14] A. Puente-Castro, E. Fernandez-Blanco, A. Pazos, and C. R. Munteanu, "Automatic assessment of Alzheimer's disease diagnosis based on deep learning techniques," Computers in biology and medicine, vol. 120, p. 103764, 2020.

[15] S. Qiu et al., "Development and validation of an interpretable deep learning framework for Alzheimer's disease classification," Brain, vol. 143, no. 6, pp. 1920–1933, 2020.

[16] "MRI and Alzheimers." Accessed: Dec. 21, 2023. [Online]. Available: https://www.kaggle.com/datasets/jboysen/mri-and-alzheimers.

[17] M. Avşar and K. Polat, "Classifying Alzheimer's disease based on a convolutional neural network with MRI images," Journal of Artificial Intelligence and Systems, vol. 5, no. 1, pp. 46–57, 2023.

[18] D. Dablain, B. Krawczyk, and N. V. Chawla, "DeepSMOTE: Fusing deep learning and SMOTE for imbalanced data," IEEE Transactions on Neural Networks and Learning Systems, 2022.

[19] G. Nirmalapriya, V. Agalya, R. Regunathan, and M. B. J. Ananth, "Fractional Aquila spider monkey optimization based deep learning network for classification of brain tumor," Biomedical Signal Processing and Control, vol. 79, p. 104017, 2023.

[20] "A deep learning based CNN approach on MRI for Alzheimer's disease detection - IOS Press." Accessed: Feb. 24, 2024. [Online]. Available: https://content.iospress.com/articles/intelligent-decision-technologies/idt190005.

[21] "Ensemble of CNN Models for Identifying Stages of Alzheimer's Disease: An Approach Using MRI Scans and SMOTE Algorithm | IEEE Conference Publication | IEEE Xplore." Accessed: Feb. 24, 2024. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10213182.