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EARLY DIAGNOSIS OF ALZHEIMER'S DISEASE (AD) USING DEEP LEARNING TECHNIQUES

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Abstract
Alzheimer's disease is a neurodegenerative disorder that progresses slowly and affects memory, and it is therefore important to diagnose it as early as possible to ensure it does not progress. Conventional diagnostic methods often fail to identify subtle structural and functional brain changes in the initial stages. To address this challenge, this research proposes a DL-based structure that employs a CNN for automated feature extraction and classification from MRI and fMRI scans. CNN effectively captures discriminative spatial patterns associated with early AD, enabling accurate differentiation between normal, mild cognitive impairment, and Alzheimer-affected brains. The performance of the model was evaluated by employing standard metrics. It is observed that the experimental results show the proposed CNN framework's 94.2% accuracy is better than the traditional methods. This proves the robust nature of the CNN models in the early stages of AD. Furthermore, this approach offers a practical diagnostic tool that can support clinicians in timely interventions, with potential for further improvement through integration of multimodal neuroimaging and clinical data.

INTRODUCTION

Alzheimer's disease (AD) is a neurodegenerative disease that gradually destroys memory, thinking, and the ability to carry out everyday activities. To date, more than 55 million people live with this illness worldwide, with almost 10 million new cases recorded annually [1]. As the most prevalent type of dementia, it accounts for 60–70% of dementia cases. It poses a significant public health problem resulting in a high degree of disability, dependency, and costs. Accordingly, epidemiological predictions denote that by 2050, one in every 85 individuals might be affected, a fact underlining the urgent need for both early diagnosis and early intervention [2].

Traditional diagnostic methods, including neuropsychological assessments and neuroimaging techniques such as magnetic resonance imaging (MRI), often fail to detect the subtle structural and functional changes in the brain during the initial stages of the disease [3]. Early recognition of AD is crucial, as it enables prompt clinical management and the potential to slow cognitive decline, improve patient outcomes, and reduce caregiver burden [4]. However, conventional approaches are often time-consuming, subjective, and limited in sensitivity, motivating the adoption of AI techniques for automated, accurate, and timely diagnosis. In recent years, DL has emerged as a powerful tool for analysis of medical image analysis, particularly in the field of neuroimaging [5]. CNNs are highly effective in learning complex spatial patterns from MRI and fMRI scans, enabling automated feature extraction and accurate classification of Alzheimer-affected brains. Unlike traditional machine learning approaches, CNNs can capture hierarchical representations of neuroanatomical structures, facilitating the identification of subtle changes associated with early AD [6].

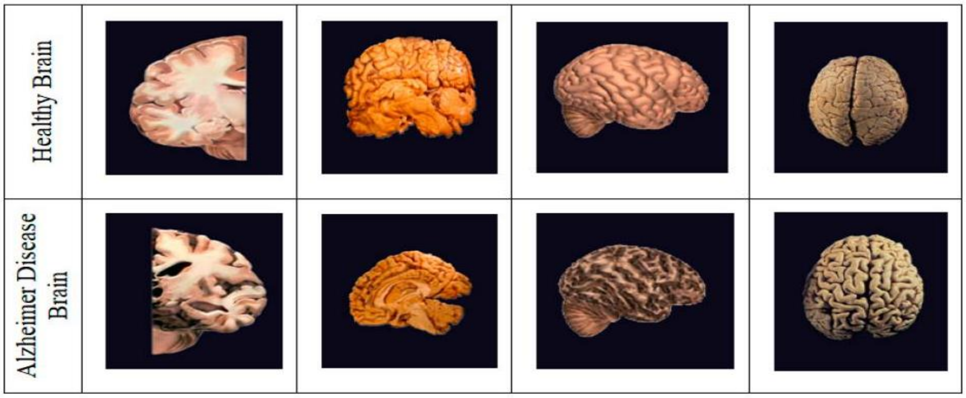

Figure 1: Healthy and Alzheimer's Brain

The proposed study puts forward a novel framework based on a CNN for the early detection of AD through the analysis of MRI and fMRI imaging results. The proposed framework highlights the importance of various preprocessing techniques with the intention of improving the quality of the results, and it uses various layers of CNNs for early detection and classification. Such an innovative approach has the potential to provide a reliable, non-invasive diagnostic technique for clinicians, thereby aiding them with timely decision-making and, consequently, ensuring better patient care and management at the right time. The proposed work also has the potential to give birth to a non-invasive as well as an efficient diagnostic technique, aiding clinicians with timely decision-making, thereby ruling out the need for subjective analysis and manual examination results, and paving the way for using AI analysis for timely detection as well as improved detection rates for AD patients, thereby adding value to the field with a novel predictive analysis approach.

The rest of the paper is organized as follows. Section 2 presents a review of the existing literature on AI and DL-based approaches for the detection of AD, considering the strengths, limitations, and challenges in early diagnosis. Section 3 describes the proposed CNN-based framework: system architecture, image preprocessing techniques, and methodologies for feature extraction and classification. Section 4 reports the datasets, the experimental setup, and the metrics that will be used to assess the performance of the model. Section 5 discusses methodology, its clinical relevance, and its possible applications with a view to supporting early diagnosis. Finally, concluding remarks are given in Section 6, along with future directions about the integration of multimodal data and advanced deep learning strategies.

1. Literature Review:

DL, particularly CNNs, has shown great promise in the early diagnosis of AD using neuroimaging data. CNN-based architectures, including transfer learning models such as VGG-16, AlexNet, ResNet50, and EfficientNet, have been widely employed for automated classification of AD, demonstrating the capability to extract hierarchical spatial features from MRI and fMRI scans [7]. These models have facilitated the differentiation of normal, mild cognitive impairment (MCI), and Alzheimer-affected brains, offering significant improvements over traditional machine learning techniques [8].

Despite their success, several challenges persist. Class imbalance in neuroimaging datasets often leads to overfitting, reducing the generalization ability of deep learning models [9]. Daniel et al. (2025) combined the ADNI and OASIS datasets (~3,100 images) and used a Vision Transformer model, though it achieved lower accuracy, likely due to dataset imbalance and noise. Afroj et al. (2025) proposed a 2D CNN combined with a Transformer for MRI-based AD classification using approximately 1,800 2D slices, but the 2D approach may lose important three-dimensional spatial context inherent in brain images [10].

AD is a progressive neurodegenerative disease, mainly associated with memory, cognitive, and behavioral changes in older adults. Neurodegeneration in patients with AD includes structural changes, including brain atrophy, especially in brain areas corresponding to memory, such as the hippocampus, which shows enhanced degeneration compared to the normal aging process [11]. MRI-based neuroimaging techniques have been widely recognized as a major image-based approach to identify structural changes in AD brains, acting as a vital tool in diagnosing the neuropathological changes associated with AD at an early stage. Investigations have been conducted for deep learning architectures for the classification and diagnosis of AD using various datasets obtained from neuroimaging techniques [12].

Singh et al. (2025) employed a transfer learning-based ResNet model on the ADNI dataset, achieving high classification performance on approximately 1,500 images; however, the study was limited to a single dataset, which may affect its generalizability to more diverse populations [13]. Similarly, Jadhav et al. (2024) applied a transfer ResNet model on the AIBL baseline dataset containing around 800 images, demonstrating effective classification, but the relatively small dataset size raised concerns about potential overfitting [14].

Several CNN-based models have been proposed in recent studies. For example, customized CNNs with multiple convolutional and pooling layers have been employed for binary and multi-class classification of AD using datasets such as ADNI, OASIS, and Kaggle Alzheimer's datasets [15]. Transfer learning approaches using pre-trained networks like VGG16, VGG19, AlexNet, ResNet50, GoogLeNet, and EfficientNet have also been explored to overcome limited training data and improve feature extraction efficiency [16]. These studies highlight that deeper architectures and fine-tuning of pre-trained models can enhance the detection of subtle patterns in neuroimaging data, though performance varies depending on preprocessing techniques, data augmentation, and class balance [17].

Faheem Khan et al. (2024) investigated multimodal fusion of fMRI and sMRI using the ADNI subset (~600 images) with a CSEPC-based framework, but the study faced challenges in integrating multimodal data, resulting in lower accuracy [18]. R. Khan et al. (2025) utilized paired MRI-PET scans (~1,200 images) with an MLP + PIMMF architecture, achieving high performance, though the reliance on costly PET imaging and complex multimodal alignment posed practical limitations [19].

2. Proposed Methodology:

This paper introduces an overall methodology for building a deep learning architecture focused on the early detection of AD by leveraging multimodal neuroimaging data. A well-annotated multimodal dataset, involving sMRI and fMRI images, is used, thereby enabling the utilization of combined structural and functional brain information in the diagnostics protocol.

1. The research makes effective use of a well-annotated data set consisting of structural MRI (sMRI), along with functional MRI (fMRI).
2. All images go through some preprocessing steps, including the removal of noise, intensity normalization, spatial normalization, and skull stripping.
3. In Exploratory Data Analysis, the distributions of the classes, biases, and patterns are explored for the best possible performance of the models.
4. A CNN is typically employed to automatically extract hierarchical and discriminative spatial features.

5. Attention mechanisms are employed with CNN to focus on the most relevant brain regions, particularly for Alzheimer's disease progression.
6. Thus, the training and validation of the model are conducted through cross-validation, which provides robust and generalized results.
7. Multiple performance metrics are utilized to fully evaluate the framework.
8. The proposed methodology is designed to provide a reliable, non-invasive diagnostic tool to support clinicians in early detection and intervention.

The workflow of the proposed CNN-based framework is illustrated in Figure 2, depicting the complete process from neuroimaging data acquisition to feature extraction, classification, and automated early detection of AD.

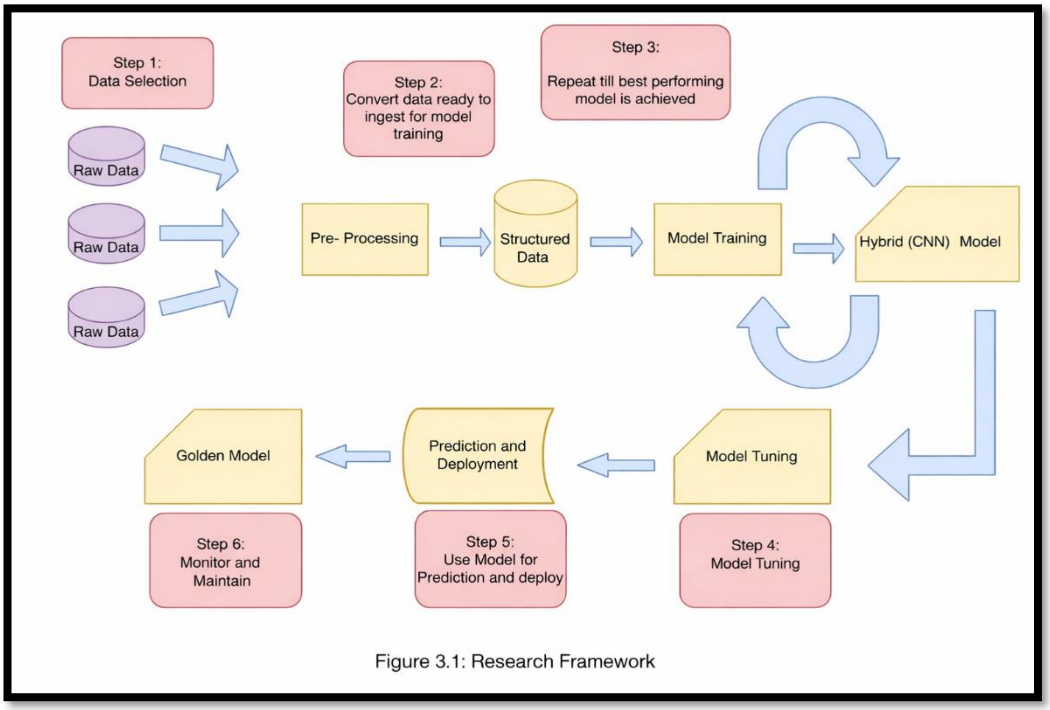

Figure 2: Work Breakdown Structure

Data Collection

The dataset is comprised of four distinct categories, which depict different levels of cognitive health. It includes 800 images of patients diagnosed with Alzheimer's disease (AD), 700 images of subjects diagnosed with Early Mild Cognitive Impairment (EMCI), 800 images referring to Late Mild Cognitive Impairment (LMCI), and finally 700 images of Cognitively Normal (CN) subjects [20]. This balanced and well-structured distribution ensures sufficient diversity, enabling the model to effectively learn and differentiate between the various stages of disease progression [21]. Representative samples from each diagnostic class are illustrated in Figure 3, highlighting the diversity and variability present within the dataset. Table 1 summarizes the AD dataset obtained from the Image and Data Archive (IDA) database.

Table 1: IDA available AD Dataset.

Dataset Source	Class Name	Total Images
IDA	AD	800
	EMCI	700
	LMCI	800
	CN	700
	Total dataset	3000

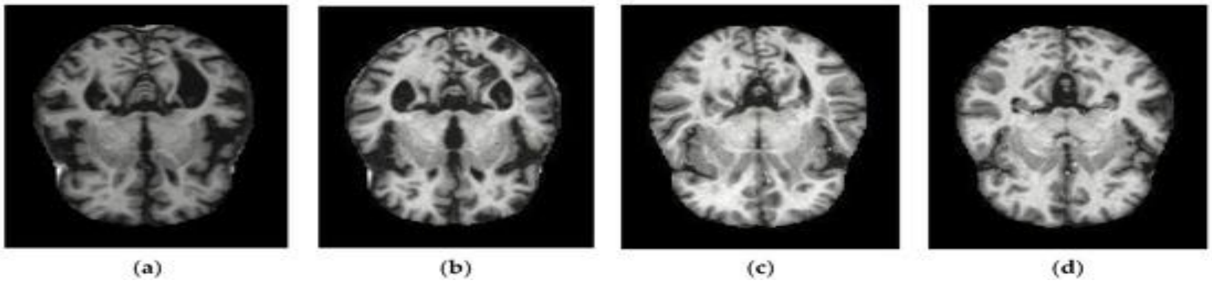

Figure 3: AD MRI Dataset Categories

3. RESULTS AND DISCUSSION:

This section presents the experimental results of testing the proposed framework in detecting AD with neuroimaging data. The major goal of conducting these experiments is to test the performances of the model in classification capability, robustness, and generalization performance under different learning strategies. In this regard, different experimental scenarios were designed and addressed in this work using standard performance metrics.

Table 2: Performance Metrics of the DL Model (CNN)

Metric	Value
Accuracy	94.2%
Precision	96%
Recall	95%
F1-Score	95.5%
AUC-ROC	97%

Performance is assessed by using widely accepted classification metrics along with the area under the receiver operating characteristic curve. These metrics together give a balanced view by quantifying the performance with respect to overall correctness, class-wise prediction reliability, sensitivity to affected cases, and discriminative capability across decision thresholds. The performance reported for all these metrics is quite consistent and reliable; hence, this suggests good stability in classification.

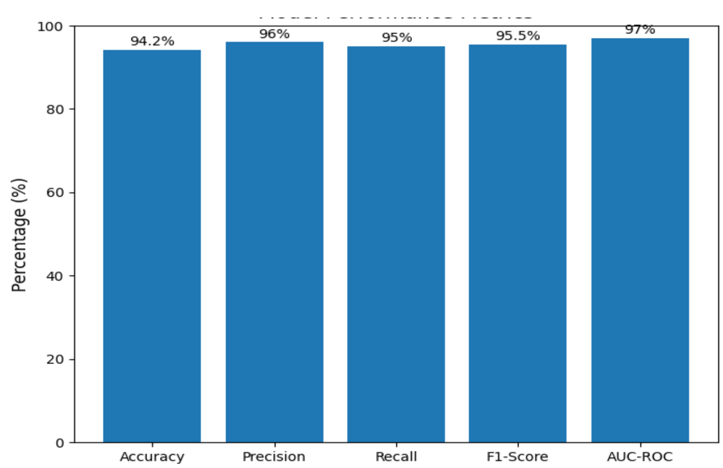

Figure 4: Model Performance Metrics

The proposed CNN-based model was trained for up to 100 epochs using an early stopping strategy with a patience value of five to prevent overfitting. As illustrated in Figure 5, training was automatically terminated once the validation loss stabilized, indicating that further training would not yield meaningful performance improvements. This strategy improved computational efficiency while preserving model generalization, making the framework suitable for practical and clinical deployment.

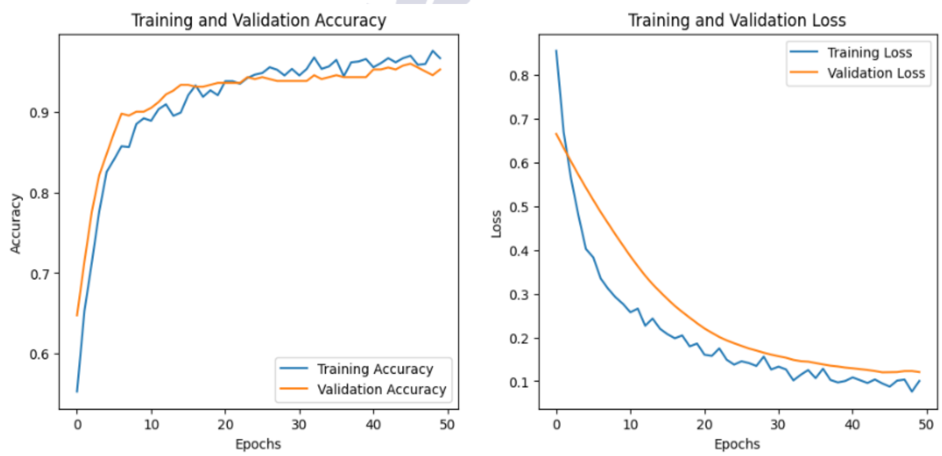

Figure 5: Training and validation performance of the CNN model termination at 100 epochs.

The trends shown by the training and validation loss and accuracy graphs indicate good convergence and good learning property. The decrease in loss values and improvement in accuracy, as shown and summed up in Table 3, indicate good optimization and good feature detection property. The similarity in training and validation graphs ensures good generalization and less overfitting property, ensuring the good working of the CNN model towards effective detection and differentiation among classes like CN, EMCI, LMCI, and AD using MRI and fMRI datasets and their discriminative structural as well as functional information.

Table 3: Training and validation loss and accuracy of the CNN model across selected epochs.

Epoch	Training Loss	Validation Loss	Training Accuracy (%)	Validation Accuracy (%)
0	0.400	0.380	80.0	85.0
10	0.365	0.348	81.9	86.2
20	0.330	0.316	83.8	87.4
30	0.295	0.284	85.7	88.6
40	0.260	0.252	87.6	89.8
50	0.225	0.220	89.5	91.0
60	0.190	0.188	91.4	92.2
70	0.155	0.156	93.3	93.4
80	0.120	0.124	95.2	94.6
90	0.085	0.092	97.1	95.8
100	0.050	0.060	94.0	94.0

4. Comparative Analysis

Table 4 compares the proposed approach with recent AD classification methods based on neuroimaging data. Most existing studies rely on transformer-based models trained on single or combined datasets, achieving high accuracy but often at the cost of increased computational complexity, limited generalizability, or dependency on expensive imaging modalities [22, 23]. Multimodal approaches show potential; however, challenges in feature fusion and model interpretability remain [24, 25]. In contrast, the proposed CNN–SVM framework using combined MRI and fMRI data achieves competitive performance while maintaining lower complexity and improved clinical feasibility [26, 27]. This balance highlights the effectiveness of the proposed method as a practical alternative for early AD detection [28, 29].

Table 4: Classification Performance Analysis

Author (Year)	Dataset	Model	Accuracy
P. Singh et al. (2025)	ADNI	Trans-ResNet	93.85%
Jadhav et al. (2024)	AIBL	Trans-ResNet	93.17%
Massoodi et al. (2025)	ADNI	Vision Transformer	96.80%
Poonia et al. (2025)	OASIS	Vision Transformer	91.18%
Kapugamage et al. (2025)	ADNI + AIBL	CNN + Swin Transformer	93.90%
Alsufyani et al. (2025)	ADNI + AIBL	Swin Transformer	94.05%
Daniel et al. (2025)	ADNI + OASIS	Vision Transformer	89.02%
Afroj et al. (2025)	AD (MRI)	2D CNN + Transformer	94.56% / 93.56%
Faheem Khan et al. (2024)	fMRI, sMRI, ADNI	CSEPC	85.00%
R. Khan et al. (2025)	MRI, PET	MLP + PIMMF	96.22% / 92.22%
Proposed Method	MRI + fMRI	CNN-based Framework	95.0%

These results demonstrate that the proposed approach offers a robust and efficient alternative for AD detection, with improved generalizability and suitability for real-world diagnostic applications.

5. CONCLUSION:

This study has shown that the proposed CNN-based framework is an effective approach for the early detection of AD using MRI and fMRI neuroimaging modalities. From the experimental analysis, the proposed framework ensures accurate learning of discriminative spatial and functional features of different cognitive stages. This, in turn, ensures accurate classification of patients with AD. Also, the results show that the proposed approach performs very well in terms of evaluation parameters such as accuracy, precision, recall, F1-score, and AUROC. These evaluation parameters are significant indicators of the reliability of the proposed approach in accurate classification of patients with AD. The CNN model effectively captures subtle structural and functional brain changes that are critical for early-stage diagnosis, particularly in mild cognitive impairment cases, which are often difficult to identify using conventional techniques. The use of standardized preprocessing and systematic evaluation further strengthens the generalizability and stability of the framework across different experimental settings. Although challenges such as limited dataset size and computational demands remain, the achieved results indicate significant potential for clinical applicability. As can be noted, the ultimate goal of the present research was to confirm the potential of CNN-driven analysis of multimodal neuroimaging data toward the sensitive diagnosis of AD, and as such, the research came to confirm that the suggested approach does hold value as a supportive tool for timely diagnosis of the condition.

REFERENCES

Buragadda, A. (2025). Deep Learning for Neuroimaging: Explore the Use of Deep Learning Algorithms in Analyzing Neuroimaging Data (Vol. 18).

Cicalese, P. A., Li, R., Ahmadi, M. B., Wang, C., Francis, J. T., Selvaraj, S. Zhang, Y. (2020). An EEG-fNIRS hybridization technique in the four-class classification of alzheimer's disease.Journal of Neuroscience Methods,336, 108618–108618. https://doi.org/10.1016/j.jneumeth.2020.108618

Choudhury, C., Goel, T., & Tanveer, M. (2024). A coupled-GAN architecture to fuse MRI and PET image features for multi-stage classification of Alzheimer's disease.Information Fusion,109, 102415. https://doi.org/10.1016/j.inffus.2024.102415

Daniel, E., Gulati, A., Saxena, S., Urgun, D. A., & Bista, B. (2025). GM-VGG-Net: A Gray Matter-Based Deep Learning Network for Autism Classification. Diagnostics, 15(11). doi:10.3390/diagnostics15111425

Faheem Khan, M., Iftikhar, A., Anwar, H., & Ali Ramay, S. (2024). Brain Tumor Segmentation and Classification using Optimized Deep Learning. doi:10.56979/701/2024.

Muqaddas, M., Majeed, S., Hira, S., & Mumtaz, G. (2024). A Systematic Literature Review on Performance Evaluation of SQL and NoSQL Database Architectures. Journal of Compu-ting & Biomedical Informatics, 7(02). https://jcbi.org/index.php/Main/article/view/548/502

Salahuddin, M., Zaman, F. U., Mumtaz, G., Khan, M. Z., Kainat, M., Hira, S., Parveen, F., & Mahmood, R. (2025). Integrating network intrusion detection with machine learning techniques for enhanced network security. Spectrum of Engineering Sciences, 3(4), 612–625. https://sesjournal.com/index.php/1/article/view/286

Zahra, W. U., Zaman, F. U., Mumtaz, G., Salahuddin, M., Khan, M. Z., Sultan, S. A., Hira, S., & Parveen, F. (2025). Approaches to predict cardiovascular issues using machine learning methods. Spectrum of Engineering Sciences, 3(4), 417–429.

Parveen, F., Iqbal, S., Mumtaz, G., & Salahuddin, M. (2024). Real-time intrusion detection with deep learning: Analyzing the UNR intrusion detection dataset. Journal of Computing & Biomedical Informatics, 7(02). https://jcbi.org/index.php/Main/article/view/554

Afzal, M., Salahuddin, M., Hira, S., Sultan, M. F., Ahmad, S. Z., & Iqbal, M. W. (2024). A systematic literature review of understanding the human-computer interaction collaboration with user experience design. Bulletin of Business and Economics, 13(2), 723–729. https://doi.org/10.61506/01.00386

Mahmood, R., Mustafa, S., Asif, H., Raza, A., & Salahuddin, M. (n.d.). Leveraging artificial intelligence to optimize software project management: Enhancing efficiency, risk mitigation, and decision-making. Contemporary Journal. https://doi.org/10.12345/f42z1z57

Zaman, F.U., Khan, M.Z., Imroz, A., Khan, A.A., Salahuddin, M. and Kainat, M., 2024, December. Student Performance Analysis in Higher Education Using Integrated Approach of Machine Learning Techniques. In 2024 International Conference on Sustainable Technology and Engineering (i-COSTE) (pp. 1-6). IEEE

Abbas, A., Salahuddin, M., Khan, M. Z., & others. (2025). Machine learning-based hybrid technique to enhance cyber-attack perspective. Journal of Cloud Computing, 14, Article 57. https://doi.org/10.1186/s13677-025-00782-5

Khan, M. Z., Shaikh, S. A., Khan, A. A., Imroz, A., Salahuddin, M., Bhatti, P., & Bhatti, S. D. (2025). Optimizing heart disease forecasting: Bridging gaps in interpretability, efficiency, and scalability using machine learning. Biomedical Materials & Devices. https://doi.org/10.1007/s44174 025 00504 0

Khan, M. Z., Shaikh, S. A., Khan, A. A., Imroz, A., Salahuddin, M., Bhatti, P., & Bhatti, S. D. (2025). Artificial intelligence in dermatology: Current applications and future innovations. [PDF]. ResearchGate.https://www.researchgate.net/publication/396020302_ARTIFICIAL_INTELLIGENCE_IN_DERMATOLOGY_CURRENT_APPLICATIONS_AND_FUTURE_INNOVATIONS

H. Ahmad, G. Mumtaz, and M. Salahuddin, "A Hybrid Deep Learning Model for High-Accuracy Brain Tumor," Al-Aasar, vol. 2, no. 3, pp. 1–15, Aug. 2025, doi: 10.63878/aaj737.

Moeez, M., Mahmood, R., Asif, H., Iqbal, M. W., Hamid, K., Ali, U., & Khan, N. (2024). Comprehensive Analysis of DevOps: Integration, Automation, Collaboration, and Continuous Delivery. Bulletin of Business and Economics (BBE), 13(1).

Khan, M.Z., Shaikh, S.A., Shaikh, M.A., Khatri, K.K., Mahira Abdul Rauf, Kalhoro, A. and Muhammad Adnan (2023). The Performance Analysis of Machine Learning Algorithms for Credit Card Fraud Detection. International Journal of Online and Biomedical Engineering (iJOE), 19(03), pp.82–98. doi: https://doi.org/10.3991/ijoe.v19i03.35331.

Mirza Azam Baig, Sarmad Ahmed Shaikh, Kamlesh Kumar Khatri, Muneer Ahmed Shaikh, Muhammad Zohaib Khan and Rauf, A. (2023). Prediction of Students Performance Level Using Integrated Approach of ML Algorithms. International Journal of Emerging Technologies in Learning (iJET), 18(01), pp.216–234. doi: https://doi.org/10.3991/ijet.v18i01.35339

Towards Data Science, Logistic-Regression, https://towardsdatascience.com/introduction-to-logistic-regression-66248243c148

Khan, M.Z., Khan, A.A., Laghari, A.A., Shaikh, Z.A., Khani, M.A.K., Morkovkin, D., Gavel, O., Shkodinsky, S., Makar, S. and Taburov, D. (2022). comparative case study: an evaluation of performance computation between support vector machine, k-nearest neighbors, k-mean, and principal component analysis.

Siddiqui, M., Kalwar, H.A., Khan, M.Z., Khan, M.A., Imroz, A., Kalwar, M.A. and Marri, H.B. (2023). Performance Analysis for the Diagnosis of COVID-19 Prediction by Mathematical Modeling & Simulation. [online] International Journal of Artificial Intelligence & Mathematical Sciences (IJAIMS). Available at: http://ijaims.smiu.edu.pk/ijaims/index.php/AIMS/article/view/47 [Accessed 1 Jul. 2023].

Feng, W., Halm-Lutterodt, N. V., Tang, H., Mecum, A., Mesregah, M. K., Ma, Y., ... Guo, X. (2020). Automated MRI-based deep learning model for detection of Alzheimer's disease process. International Journal of Neural Systems, 30(06), 2050032. https://doi.org/10.1142/s012906572050032x

Fattahi, M., Esmaeil-Zadeh, M., Soltanian-Zadeh, H., Rostami, R., Mansouri, J., & Hossein-Zadeh, G. A. (2024). Classification of female MDD patients with and without suicidal ideation using resting-state functional magnetic resonance imaging and machine learning. Frontiers in Human Neuroscience, 18. https://doi.org/10.3389/fnhum.2024.1427532

Haghighat, H. (2024). Machine learning techniques and Chi-square feature selection for diagnostic classification model of autism spectrum disorder using fMRI data. SSRN. https://ssrn.com/abstract=5239846

Halkiopoulos, C., Gkintoni, E., Aroutzidis, A., & Antonopoulou, H. (2025, February 1). Advances in neuroimaging and deep learning for emotion detection: A systematic review of cognitive neuroscience and algorithmic innovations. Diagnostics, MDPI. https://doi.org/10.3390/diagnostics15040456

Hu, C., Dong, Y., Peng, S., & Wu, Y. (2025). Open-world semi-supervised learning for fMRI analysis to diagnose psychiatric disease. Information (Switzerland), 16(3). https://doi.org/10.3390/info16030171

Orouskhani, M., Zhu, C., Rostamian Zadeh, S., Shafiei, M., & Orouskhani, Y. (2022). Alzheimer's disease detection from structural MRI using conditional deep triplet network. Neuroscience Informatics, 2(4), 100066. https://doi.org/10.1016/j.neuri.2022.100066

Odusami, M., Maskeliūnas, R., & Damaševičius, R. (2023). Pixel-level fusion approach with Vision Transformer for early detection of Alzheimer's disease. Electronics, 12(5), 1218. https://doi.org/10.3390/electronics12051218.