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MULTICLASS CLASSIFICATION OF ALZHEIMER DISEASE USING TRANSFER LEARNING TECHNIQUES

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Abstract:

Alzheimer's disease is a chronic neurological disorder that causes damage to memory and cognitive functions. Detection in its earlier stages and classification is of importance in effective treatment and management. In this paper, a transfer learning technique-based multiclass classification for distinguishing different stages of AD is proposed. We employ improved pre-trained deep learning models on a dataset of brain MRI images, classifying the diseases into several categories: Non-Demented, Very Mild Demented, Alzheimer's Mild Demented, and Moderate Demented. This paper presents an accuracy and wholesomeness in identifying stages of Alzheimer's, thus giving a light to the possibility of transfer learning in the view of medical analysis. In this research, several pre-trained deep learning models have been explored for the classification of AD, including ResNet50V2 and InceptionResNetV2. ResNet50V2 turned out to be the winner against all competitors about the classification accuracy. It achieved quite a high trainingaccuracy of 92.15% before testing at 91.25%. Quite obviously, these results show.

Keywords:
Alzheimer's Disease, Deep Learning, Transfer Learning, Convolutional Neural Network.

1. Introduction:

AD is an emerging global health issue that affects millions of people.[1-16] It is characterized by gradual loss of cognitive functions, memory, and behavioral changes. Its early, accurate diagnosis is, therefore of prime importance, to manage the disease and bring out the best in the patient. [17-31]The traditional methods used in diagnosis basically rely on clinical evaluation and neuroimaging, which are basically illogical and time-consuming. [32-43]This research is an attempt at classifying Alzheimer's disease stages according to brain MRI images with the help of transfer learning. This paper used several well-known deep learning models that were pre-trained on large image datasets like ImageNet.[44-50] One of the primary purposes of this research is to evaluate the efficiency of transfer learning in identifying the different stages of Alzheimer's disease and to draw a comparison among different models for this particular task. In neurology and gerontology, Alzheimer's disease (AD) is one of the major challenges, and increases in its prevalence with aging should be expected[51-55].We will design and evaluate the performance of a transfer-learning-based classifier for Alzheimer's disease.

2. Literature Survey:

Heta Acharya et al. (2021) [1-2]: This research aims to classify MRI of Alzheimer disease patients into multiple class by using VGG16, ResNet -50 and AlexNet as transfer learning models along with convolution neural networks. The techniques used in this research are VGG16, ResNet -50 and AlexNet as transfer learning models. The proposed strategies show results with an accuracy of 95.70%, this represents a substantial improvement in accuracy over previous studies, demonstrating the efficacy of the proposed method. And these methods are useful for AD patients to recover. In future work, examine whether the same model can be applied to other computer assisted diagnostic problems. Also, examine the progress of the intelligent classification of real-time programming training data.

Ahsan Bin Tufail et al. (2020) [3-4]: In this article, this study is geared towards understanding the performance differences between these architectures. The techniques used for this article are 2D and 3D Convolutional Neural Networks (CNNs) from PET and MRI neuroimaging modalities**.** The performance of 3D architectures to be better in comparison to their 2D counterparts. And found the performance of 3D architecture trained on PET neuroimaging modality data to be the best in terms of performance metrics which shows superior diagnostic power of this type of architecture. This study can be extended further by the inclusion of more data, additional classes such as static and progressive MCI, as well as novel architectures such as recurrent neural networks for a better understanding of the underlying disease phenomenon.

Naimul Mefraz Khan et al. (2019) [5-6]: In this paper, we attempt solving these issues with transfer learning, where the state-of-the art VGG architecture is initialized with pretrained weights from large benchmark datasets consisting of natural images. In this article we used Transfer learning where the state-of the art VGG architecture is initialized. Through experimentation we reach the state-of-the-art performance in AD vs. NC, AD vs. MCI, and MCI vs. NC classification problems, with a 4% and a 7% increase in accuracy over the state-of the-art for AD vs. MCI and MCI vs.NC, respectively.It will be investigated whether the same architecture can be employed to other computer aided diagnosis problems. And, will be investigate whether this entropy-based image selection method can be improved further by incorporating further probabilistic measures on the images.

Ahmed Arafa et al. (2023) [7-8]: In this article, two methods are implemented. The first method uses a simple CNN architecture. In the second method, the VGG16 model is the pre-trained model that is trained on the ImageNet dataset but applies the same model to the different datasets. The techniques used in this research is CNN architecture and the VGG16 model. The experimental findings demonstrate that the suggested designs achieve a promising accuracy, 99.95% and 99.99% for the proposed CNN model in the classification of the AD stage. The VGG16 pretrained model is fine-tuned and achieved an accuracy of 97.44% for AD stage classifications. In the future, they intend to apply hyperparameter optimization techniques to each model and perform multiclassification n for AD stages.

F M M Shamrat et al. (2023) [9-10]: In this article, we propose a fine-tuned convolutional neural network (CNN) classifier called Alzheimer Net, which can identify all five stages of Alzheimer’s disease and the Normal Control (NC) class. The techniques used in this research are A fine-tuned convolutional neural network (CNN) classifier called Alzheimer Net. Initially, five existing models including VGG16, MobileNetV2, Alex Net, ResNet50 and InceptionV3 were trained and tested to achieve test accuracies of 78.84%, 86.85%, 78.87%, 80.98% and 96.31% respectively. As future work, a hybrid model could be implemented on ADNI fMRI and PET datasets to diagnose the stages of Alzheimer’s disease.

Hayama et al. (2022) [11-12]: The study proposes using the DenseNet architecture for the classification of Alzheimer's disease (AD) into three classes. The Deep Learning (DL) - DenseNet Architecture are used in this article to detect the Alzheimer’s Disease. The dataset is used to evaluate the recommended methodology, showing encouraging results. The experimental results show that CNN LSTM is superior, with an accuracy percentage 99.92%. CNNs-LSTM with-Aug (Convolutional Neural Networks with Long Short-Term Memory and data augmentation) for AD identification is interpretability.

M. Leela et al. (2023) [13-14]: Specifies the primary symptoms of AD, which include forgetfulness, confusion, and difficulty with problem solving and language. HEMRDTL model and Robust Principal Component Analysis (RPCA) are the techniques used to detect the Alzheimer’s Disease. These methods can be applied to screen larger populations more effectively, addressing the growing global concern over AD prevalence and the need for widespread screening.However, the dataset of OCT images specifically from individuals with Alzheimer's disease is noted as not currently available.

Sina Fathi et al. (2023) [15-16]: It comprised of collecting the dataset, preprocessing, creating the individual and ensemble models, evaluating the models based on ADNI data and validating the trained model based on the local dataset. The study's main objective was to propose an ensemble method based on deep learning for early AD diagnosis using MRI images. The compared to individual architectures in the context of diagnosing Alzheimer's disease (AD) using MRI images.The potential limitation related to the generalizability of the deep learning (DL) framework for diagnosing Alzheimer's disease (AD) when applied to different datasets.

Hadeer et al. (2020) [17-18]: A comprehensive e overview of the framework, methods, application, performance, and future. A deep learning approach, specifically convolutional neural networks (CNN), is used in this work. Four stages of the AD spectrum are multi classified. The transfer learning principle to take advantage of the pre trained models for medical image classifications, such as the VGG19 model.The results are promising, but the text does not discuss the generalizability of the model to other datasets or real-world scenarios outside the ADNI dataset.

Ahmad Waleed Saleh et al. 2023) [19-20]: A performance baseline is created without data augmentation to address the difficulties in classifying AD due to high dimensional MRI brain scans. Our approach leverages transfer learning architectures as the base model and showcases superior performance on the MRI dataset. TL based techniques, and CNN technique. The proposed system model achieves a high accuracy of 96.5% and an impressive Area Under the Curve (AUC) of 99%, surpassing previous methods. Due to the significant processing needs of Grid Search CV, we were unable to use it.

Faizal Haja Mohideen et al. (2023) [21-25]: The model uses both pre trained and non-pretrained CNNs to convert images into the embedding space. The technique used is Siamese Convolutional Neural Network (SCNN). Demonstrated high accuracy on both ADNI (91.83%) and OASIS (93.85%) datasets, indicating reliable performance. The performance of the model relies heavily on the quality and quantity of MRI images available in the datasets.

Yang G et al. (2020) [26-29]: Used for unsupervised learning to perform the AD vs. NC classification task. The technique used in this research is Convolutional Autoencoder (CAE). Achieved accuracies of 86.60% for AD and 73.95% for PMCI classification tasks, outperforming other network models. Achieved accuracies of 86.60% for AD and 73.95% for PMCI classification tasks, outperforming another network. The performance of the model relies heavily on the quality and quantity of MRI images available in the datasets.

Ahmad Waleed Saleh Et al (2023) [30-34]: A performance baseline is established without data augmentation to address the challenges posed by high dimensional MRI brain scans. Convolutional Neural Network (CNN) techniques is used in this research. The model achieves high accuracy (96.5%) and an impressive AUC (99%), indicating robust performance. Although transfer learning mitigates some issues, training CNNs, including DenseNet, can still be time consuming and resource intensive. The model's performance relies on the availability and quality of neuroimaging data.

V Adarsh et al (2024) [35-37]: The model shows unmatched diagnostic accuracy with a classification efficacy of 98.27%. Convolutional Neural Networks (CNN) technique is used in this research. Achieves a classification efficacy of 98.27%, indicating exceptional performance.The model's performance relies on the availability and quality of neuroimaging data. Although transfer learning mitigates some issues, training CNNs, including DenseNet, can still be time consuming and resource intensive.

Manu Raju et al (2021) [38-40]: The approach utilizes transfer learning with the VGG16 architecture, a pretrained Convolutional Neural Network (CNN), to perform the classification. The technique used in this article is Transfer Learning with VGG16 Fast air Library. The approach achieves 99% predictive accuracy, which is a significant improvement compared to previous studies.The model's performance heavily relies on the availability and quality of labelled MRI data for training.

Hadeer A. Helaly et al. (2021) [41-42]: A deep learning approach, specifically convolutional neural networks (CNN), is used in this article. The main objective is to design an end-to-end framework for early detection of Alzheimer’s disease and medical image classification for various AD stages. Deep learning approach, specifically convolutional neural networks (CNN) technique is used here. They achieve very promising accuracies, 93.61% and 95.17% for 2D and 3D multiclass AD stage classifications. The VGG19 pretrained model is fine-tuned and achieved an accuracy of 97% for multi class AD stage classifications.In the future, it is planned to apply other pretrained models such as Efficient Net B0 to B7 for multiclass AD stage classifications and check the performance.

Y Puspa Rani et al. (2023) [43-44]: This study aims to see which views of MRI images have higher accuracy for AD classification. Then, to get the value of three views and categories, we used multiclass classification with the publicly available Alzheimer’s Disease Neuroimaging Initiative (ADNI) dataset using Resnet50 and LeNet. The technique used in this reference is Alzheimer’s Disease Neuroimaging Initiative (ADNI) dataset using Resnet50 and LeNet. This method improves the accuracy of machine learning, and the coronal view showed higher accuracy. This method played a significant role in improving the accuracy of machine learning performance. In future studies may label the MRI slices for a fully automatic system to detect select slices containing landmarks in the hippocampus region. And, we could increase our accuracy and generate more training data using data augmentation.

Ghazala Hcini et al. (2024) [45-46]: While previous reviews have covered similar topics, this paper offers a unique perspective by providing a detailed comparison of CNN and VIT for AD classification, highlighting the strengths and limitations of each approach. While previous reviews have covered similar topics, this paper offers a unique perspective by providing a detailed comparison of CNN and VIT for AD classification, highlighting the strengths and limitations of each approach. Convolutional Neural Networks (CNN) and Vision Transformers (VIT) technique is used. CNNs can have multiple convolutional, activation, and pooling layers to learn more complex features and improve classification accuracy. This review aims to provide valuable insights for future research and clinical applications, ultimately advancing the field of AD classification using deep learning techniques.By acknowledging these challenges, the review aims to foster informed decision making and guide future research effectively.

F Haja Mohideen et al. (2023) [47-48]: In this article, they propose a Siamese Convolutional Neural Network (SCNN) architecture that employs the triplet loss function for the representation of input MRI images as k dimensional embeddings. The technique used is Siamese Convolutional Neural Network (SCNN) architecture. Early diagnosis of the disease will reduce the suffering of the patients and their family members. The model efficacy was tested using the ADNI and OASIS datasets which produced an accuracy of 91.83% and 93.85%, respectively. In the future, we can do several extensions from the proposed work. One can conduct a thorough performance evaluation using various pretrained networks such as GoogleNet, AlexNet, ResNet and its variants, etc., to determine how well the Siamese model generalizes in the 4-way classification of AD.

Uddin K.M.M et al. (2023) [49-50]: This paper proposes a machine learning model that comprises Gaussian NB, Decision Tree, Random Forest, XG Boost, Voting Classifier, and Gradient Boost to predict Alzheimer's disease. A machine learning model that comprises Gaussian NB, Decision Tree, Random Forest, XG Boost, Voting Classifier, and Gradient Boost. Early diagnosis and treatment of AD help patients to recover from it successfully and with the least harm. The voting classifier attained the highest validation accuracy of 96% for the AD dataset.To improve the detection approaches' accuracy, future research will focus on removing redundant and unneeded characteristics from existing feature sets as well as on extracting and analysing unique features that are more likely to aid in the detection.

3. Proposed Methodology:

CNN has various layers, including convolutional, non-linearity, pooling and fully connected layers. The convolutional and fully connected layers have factors, but the pooling and non-linearity layers do not have parameters.The convolution for one pixel can be calculated through the convolutional layer using Equation 1.

net $(i, j) = (x*w)[i, j] = \sum\sum mnx[m, n] \times w[i-m, j-n]$, (1)

where net(i,j) is the yielding of convolutional layer that forward it to the following layer, x indicates the input data composed of a set of images, w is the kernel or filter matrix and the asterisk represents the convolution process. However, the rectified linear unit (ReLU) has simpler descriptions of both the functions and gradient, as shown in the following two equations:

ReLU$(x) = max\ (0, x)$(2)
ddx ReLU(x) = {1 if $x > 0$; 0 otherwise}(3)

The last layer in the presented model is the SoftMax layer, which is used to compute the probability distribution of N-dimensional vectors for the input images. Equation 4 expresses the SoftMax function as follows:

$Oi = ezi \sum ezMii = 1$(4)

where Oi is the SoftMax output number i, zi is the output i before the SoftMax and M represents the overall amount of output neurons. The ultimate output is produced by the completely connected layer. With a few exceptions, CNN architectures all have the same structure

3.1 Algorithm:

In this section, we will create simple CNN model that demonstrate Convolutional layers, nonlinearity layer, Pooling layers, Fully Connected layers and SoftMax. The algorithm for the CNN model using its layers is as follows:

Step-1: Start with the convolution for one pixel can be calculated through the convolutional layer using Equation (1).

Step-2: After the mathematical operation was performed through the convolutional layer, the output of the process was forwarded to the next layer, which is the non-linearity layer.

Step-3: The rectified linear unit (RELU) has simpler descriptions of both the functions and gradient and it can be calculated from equation (2) and (3).

Step-4: The pooling layer can be investigated.

Step-5: With the help of fully connected layer, run the model.

Step-6: Thus, the output of fully connected layer that the excluded neurons and connections can be performed by using the dropout layer.

Step-7: To compute the probability distribution of N-dimensional vectors for the input images, and to obtain the output neurons runthe model with SoftMax layer of equation (4).

Step-8: End of the operation.

4. Results and Discussions:

Performance measurement was used to examine the proposed diagnostic system for AD. The equations for these metrics are as follows:

Accuracy = (TP+TN) /(FP+FN+TP+TN) (6)

Specificity = [TN/ (TN+FP)] × 100%(7)

Sensitivity = [TP/(TP+FN)] × 100%(8)

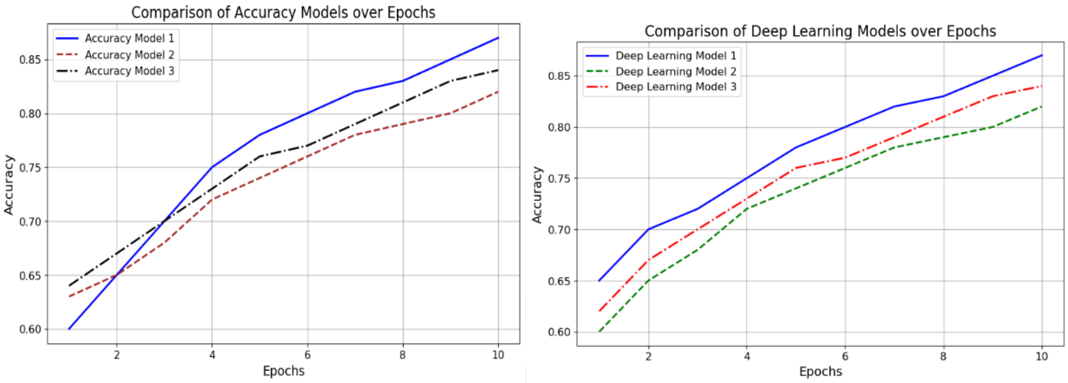
Precision = [TP/(TP+FP)] × 100% (9)

Recall = [TP/(TP+FN)] × 100% (10)

F1 score = 2 ∗ [(precision∗Recall)/ (precision∗ Recall)] × 100% (11)

where TP represents true positive; FP, false positive; TN, true-negativeimages;and FN, a false negative.

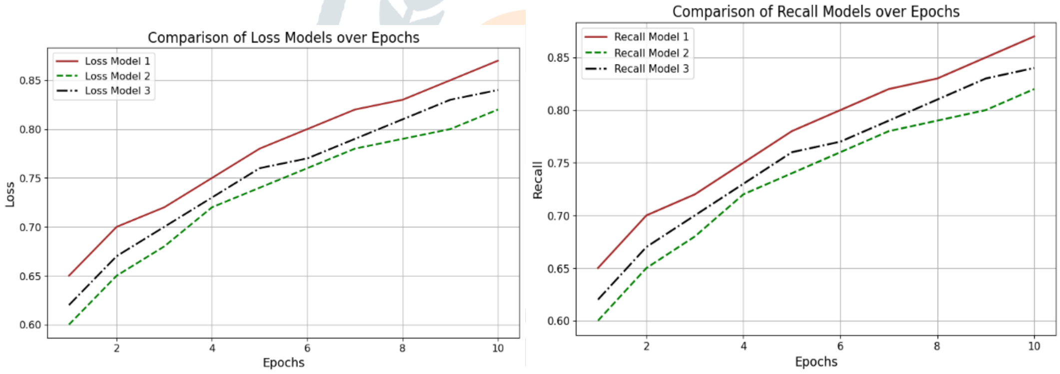
- This graph1 determines the relation between the accuracy levels at various data which is relevant and graph2 determines relation between the deep learning models over epochs.



Graph-1&2: Comparison of accuracy models and Epochs, and of deep learning over epochs

As can be seen from the graph-1, all three model's accuracy increases with the number of epochs. And graph-2 could be used to compare the performance of different deep learning models for Alzheimer's disease classification.

- Graph3 determines the relation between the loss models over epochs and graph4 determines the relation between the Recall models over epochs.



Graph-3&4: Comparison of Loss levels over epochs and Recall levels over epochs

As seen in the graph-3 Loss Model-1 has the lowest loss value throughout the epochs, indicating that it performs better than the other two models. The graph-4 also shows that the recall levels of all threemodels increase as the number epochs increases.

5. Conclusion:

The paper presents an effective Alzheimer's phase identification method using a transfer learning-based classification model. This approach fine-tunes the CNN for binary-class and multi-class issues using a pre-trained AlexNet network. For binary-class and multi-class issues, the accuracy of the model was 89.6% and 92.8%, respectively. Other designs of CNN and optimization of convolutional layers will remain as future work. This paper proposes a deep learning-based model for multiclass classification at phases of AD using transfer learning techniques. Below, we read references on techniques used for multiclass classification of AD. We further compared the classifier performance with the physician's decision and achieved good results. In this research, several pre-trained deep learning models have been explored for the classification of AD, including ResNet50V2 and InceptionResNetV2. ResNet50V2 turned out to be the winner against all competitors about the classification accuracy. It achieved quite a high trainingaccuracy of 92.15% before testing at 91.25%. Quite obviously, these results show.

We have taken a number of well-known deep learning models that are pre-trained on large image datasets like ImageNet: VGG16, ResNet50, AlexNet, and InceptionV3. Basically, the estimation of the effectiveness of transfer learning in correctly identifying Alzheimer's stages and a comparison of the performance of different models in this regard are the objectives of this study.

6. References:

1. Acharya, H., Mehta, R., & Singh, D. K. (2021, April). Alzheimer disease classification using transfer learning. In 2021 5th International Conference on Computing Methodologies and Communication (ICCMC) (pp. 1503-1508). IEEE.
2. Tufail, A. B., Ma, Y., & Zhang, Q. N. (2020, June). Multiclass classification of initial stages of Alzheimer's Disease through Neuroimaging modalities and Convolutional Neural Networks. In 2020 IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC) (pp. 51-56). IEEE
3. Khan, N. M., Hon, M., & Abraham, N. Transfer Learning with intelligent training data selection for prediction of Alzheimer’s Disease. arXiv 2019. arXiv preprint arXiv:1906.01160.
4. Arafa, D. A., Moustafa, H. E. D., Ali, H. A., Ali-Eldin, A. M., & Saraya, S. F. (2024). A deep learning framework for early diagnosis of Alzheimer’s disease on MRI images. Multimedia Tools and Applications, 83(2), 3767-3799.
5. Patibandla, R. S. M. L., Rao, B. T., Narayana, V. L., & Srinivas, V. S. (2021). An overview of ontology-based artificial intelligence services in health care systems. In Proceedings of the International Conference on Health Care Systems (pp. 47–63).
6. Maddumala, V. R., Maha Lakshmi, K., Anusha, P., & Lakshman Narayana, V. (2020). Enhanced morphological operations for improving the pixel intensity level. Journal of Computational and Theoretical Nanoscience, 29(3), 9191–9201.
7. Narayana, V. L., Malleswari, K. S. N., Divyanjali, M., Nandini, S., & Purnima, G. (2023). Video frame based prompt compression model with steganography for secure data transmission. In Proceedings of the International Conference on Advanced Intelligent Systems (pp. 373–377). https://doi.org/10.1109/ICAIS56108.2023.10073883
8. Naresh, A., Pavani, V., Meghana Chowdary, M., & Lakshman Narayana, V. (2020). Energy consumption reduction in cloud environment by balancing cloud user load. Journal of Critical Reviews, 7(7), 1003–1010. https://doi.org/10.31838/jcr.07.07.184
9. Patibandla, R. S. M. L., & Vejendla, L. N. (2022). Significance of blockchain technologies in industry. In Advances in Blockchain Technologies (pp. 19–31). https://doi.org/10.1007/978-3-030-70501-5_2
10. Pasala, S., Pavani, V., Lakshmi, G. V., & Narayana, V. L. (2020). Identification of attackers using blockchain transactions using cryptography methods. Journal of Critical Reviews, 7(6), 368–375. https://doi.org/10.31838/jcr.07.06.65
11. Mounika, B., Anusha, P., Narayana, V. L., & Lakshmi, G. V. (2020). Use of blockchain technology in providing security during data sharing. Journal of Critical Reviews, 7(6), 338–343. https://doi.org/10.31838/jcr.07.06.59
12. Narayana, V. L., Vinayaki, K. V., Swetha, P. A., Sri, K. D., & Chaithanya, G. (2024). Superior attribute weighted set for object skeleton detection using ResNet50 with edge-based segmentation model. In Proceedings of the International Conference on Smart Computing and Systems (pp. 1132–1139). IEEE. https://doi.org/10.1109/ICSCSS60660.2024.10624879
13. Gopi, A. P., & Naik, K. J. (2022). An IoT model for fish breeding analysis with water quality data of pond using modified multilayer perceptron model. 2022 International Conference on Data Analytics for Business and Industry (ICDABI), 448-453. https://doi.org/10.1109/ICDABI56818.2022.10041617
14. Arepalli, P. G., & Naik, K. J. (2024). A deep learning-enabled IoT framework for early hypoxia detection in aqua water using lightweight spatially shared attention-LSTM network. Journal of Supercomputing, 80(2), 2718-2747. https://doi.org/10.1007/s11227-023-05580-x
15. Arepalli, P. G., & Naik, K. J. (2023). An IoT-based water contamination analysis for aquaculture using lightweight multi-headed GRU model. Environmental Monitoring and Assessment, 195(12), Article 1516. https://doi.org/10.1007/s10661-023-12126-4
16. Gopi, A. P., Gowthami, M., Srujana, T., Gnana Padmini, S., & Durga Malleswari, M. (2023). Classification of denial-of-service attacks in IoT networks using AlexNet. In Smart Innovation, Systems and Technologies (Vol. 316, pp. 349-357). https://doi.org/10.1007/978-981-19-5403-0_30
17. Bikku, T., Gopi, A. P., & Prasanna, R. L. (2019). Swarming the high-dimensional datasets using ensemble classification algorithm. In Advances in Intelligent Systems and Computing (Vol. 815, pp. 583-591). https://doi.org/10.1007/978-981-13-1580-0_56

18. Arepalli, P. G., & Khetavath, J. N. (2024). Water quality classification using multi-cell RNN in aquaculture ponds for Catla fish. In Lecture Notes in Networks and Systems (Vol. 897, pp. 363-370). https://doi.org/10.1007/978-981-99-9704-6_34

19. Arepalli, P. G., & Naik, K. J. (2024). Water contamination analysis in IoT-enabled aquaculture using deep learning-based AODEGRU. Ecological Informatics, 79, Article 102405. https://doi.org/10.1016/j.ecoinf.2023.102405

20. Arepalli, P. G., & Naik, K. J. (2024). An IoT-based smart water quality assessment framework for aqua-ponds management using Dilated Spatial-temporal Convolution Neural Network (DSTCNN). Aquacultural Engineering, 104, Article 102373. https://doi.org/10.1016/j.aquaeng.2023.102373

21. Gopi, A. P., Narayana, V. L., & Kumar, N. A. (2018). Dynamic load balancing for client-server assignment in distributed systems using genetic algorithm. Ingenierie des Systemes d'Information, 23(6), 87-98. https://doi.org/10.3166/ISI.23.6.87-98

22. Sarada, K., Narayana, V. L., Gopi, A. P., & Pavani, V. (2020). An iterative group based anomaly detection method for secure data communication in networks. Journal of Critical Reviews, 7(6), 208-212. https://doi.org/10.31838/jcr.07.06.39

23. Narayana, V. L., Gopi, A. P., & Chaitanya, K. (2019). Avoiding interoperability and delay in healthcare monitoring system using blockchain technology. Revue d'Intelligence Artificielle, 33(1), 45-48. https://doi.org/10.18280/ria.330108

24. Gopi, A. P., Jyothi, R. N. S., Narayana, V. L., & Sandeep, K. S. (2023). Classification of tweets data based on polarity using improved RBF kernel of SVM. International Journal of Information Technology, 15(2), 965-980. https://doi.org/10.1007/s41870-019-00409-4

25. Narayana, V. L., Gopi, A. P., Khadherbhi, S. R., & Pavani, V. (2020). Accurate identification and detection of outliers in networks using group random forest methodology. Journal of Critical Reviews, 7(6), 381-384. https://doi.org/10.31838/jcr.07.06.67

26. Rao, B. T., Patibandla, R. S. M. L., Narayana, V. L., & Gopi, A. P. (2021). Medical data supervised learning ontologies for accurate data analysis. In Semantic Web for Effective Healthcare Systems (pp. 249-267). https://doi.org/10.1002/9781119764175.ch11

27. Patibandla, R. S. M. L., Gopi, A. P., Narayana, V. L., & Rao, B. T. (2023). Decentralized smart healthcare systems using blockchain and AI. In Blockchain applications in healthcare: Innovations and practices (Vol. 1, pp. 139-154). DOI: 10.1002/9781394229512.ch8

28. Lakshman Narayana, V., & Gopi, A. P. (2020). Enterotoxigenic Escherichia coli detection using the design of a biosensor. Journal of New Materials for Electrochemical Systems, 23(3), 164-166. DOI: 10.14447/jnmes.v23i3.a02

29. Rani, B. M. S., Majety, V. D., Pittala, C. S., Vijay, V., Sandeep, K. S., & Kiran, S. (2021). Road Identification Through Efficient Edge Segmentation Based on Morphological Operations. Traitement du Signal, 38(5).

30. Sukanya Konatam et al., (2024), A Journal on Securing NoSQL Databases: A Comprehensive Guide to Best Practices and Configurations, Paideuma Journal of Research 17 (8 2024), 15-27.

31. .Kanumalli, S. S., Ch, A., & Murty, P. S. R. C. (2020). Secure V2V Communication in IOV using IBE and PKI based Hybrid Approach. International Journal of Advanced Computer Science and Applications, 11(1).

32. 3.Kiran, S., Kanumalli, S. S., Krishna, K. V. S. S. R., & Chandra, N. (2021). WITHDRAWN: internet of things integrated smart agriculture for weather predictions and preventive mechanism.

33. Chaitanya, Kosaraju, and Sankara Narayanan. "Security and Privacy in Wireless Sensor Networks Using Intrusion Detection Models to Detect DDOS and Drdos Attacks: A Survey." 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS). IEEE, 2023.

34. Krishna, Komanduri Venkata Sesha Sai Rama, et al. "Classification of Glaucoma Optical Coherence Tomography (OCT) Images Based on Blood Vessel Identification Using .CNN and Firefly Optimization." Traitement du Signal 38.1 (2021).

35. Chaitanya, Kosaraju, et al. "Predicting the Spread of Covid Disease Based on Chest X-Ray Images Using Convolutional Neural Network with Improved Accuracy." 2023 6th International Conference on Advances in Science and Technology (ICAST). IEEE, 2023.

36. Ekkurthi, A., Sujatha, V., Kumar, K.V.,"Effective Moving Object Tracking Using Adaptive Background Subtraction with Advanced Probability Evolutionary Algorithm",International Journal on Recent and Innovation Trends in Computing and Communication, 2023, 11, pp. 1–3

37. Sujatha, V., Yaddala, M., Kollipara, V., Shaik, K., Burri, R.K(23),"Movie reviews data classification using convolution neural networks",AIP Conference Proceedings. 2023, 2724, 030009

38. Godavarthi, B., Majety, V. D., Mrudula, Y., & Nalajala, P. (2019). Fault identification in power lines using GSM and IoT technology. Advances in Intelligent Systems and Computing, 815, 647–655. https://doi.org/10.1007/978-3-319-91117-2_70

39. Majety, V. D., & Murali, G. (2018). A remote epileptic patient supervising system. Advances in Modelling and Analysis B, 61(4), 207–210. https://doi.org/10.18280/ama_b.610402

40. Naresh, A., TSLP, H., Ch, G., & Kumari, G. R. P. (2023, July). Early Prophecy of Low-Birth-Weight Babies Using BM Error Rate Classifier. In 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-6). IEEE.

41. Kumari, G. R. P., Reddy, A. H., Lakshmi, K., Abhinaya, B., Sanjana, S., & Naresh, A. (2024, March). Time-Frame-Based Drowsiness Detection System Using CNN. In 2024 2nd International Conference on Disruptive Technologies (ICDT) (pp. 711-716). IEEE.

42. V. Pavani, K. Divya, V. V. Likhitha, G. S. Mounika and K. S. Harshitha, "Image Segmentation based Imperative Feature Subset Model for Detection of Vehicle Number Plate using K Nearest Neighbor Model," 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS), Coimbatore, India, 2023, pp. 704-709, doi: 10.1109/ICAIS56108.2023.10073848.

43. V. Pavani, M. N. Swetha, Y. Prasanthi, K. Kavya and M. Pavithra, "Drowsy Driver Monitoring Using Machine Learning and Visible Actions," 2022 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2022, pp. 1269-1279, doi: 10.1109/ICEARS53579.2022.9751890.

44. Sri, Kurra Santhi, et al. "Advanced system control with traffic handling for secure communication in IoT routing protocol." Journal Européen des Systèmes Automatisés 54.2 (2021): 229-233.

45. Arumugham, Vinothini, et al. "An explainable deep learning model for prediction of early-stage chronic kidney disease." Computational Intelligence 39.6 (2023): 1022-1038.

46. Majety, Vasumathi Devi, et al. "Enhanced secure communication AODV routing protocol using SVM in MANETS." AIP Conference Proceedings. Vol. 2724. No. 1. AIP Publishing, 2023.

47. Krisha, P.S., Peram, S.R. (2023). CT image precise denoising model with edge based segmentation with labeled pixel extraction using CNN based feature extraction for oral cancer detection. Traitement du Signal, Vol. 40, No. 3, pp. 1297-1304. https://doi.org/10.18280/ts.400349

48. P. S. Krishna, V. R. Aparna, V. Priyanka, P. T. Niharika and T. Shivangi, "Convolution Neural Network Model with Feature Linked Vector for Oral Cancer Detection," 2023 IEEE 12th International Conference on Communication Systems and Network Technologies (CSNT), Bhopal, India, 2023, pp. 304-308, doi: 10.1109/CSNT57126.2023.10134660.

49. Rayachoti, Eswaraiah, Sudhir Tirumalasetty, and Silpa Chaitanya Prathipati. "SLT based watermarking system for secure telemedicine." Cluster Computing 23.4 (2020): 3175-3184.

50. Eswaraiah, Rayachoti, Tirumalasetty Sudhir, and Prathipati Silpa Chaitanya. "Curvelet transform based watermarking for telemedicine." Wireless Personal Communications 122.1 (2022): 309-329.

51. Varshini, Y., Mounika, T., Kumari, G. R. P., Sirisha, G., & Deepthi, Y. (2023, March). Crop Yield Forecast Using Machine Learning. In 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 2310-2315). IEEE.

52. B. Aruna Kumari "Time Series Data Classification for Precise Stock Market Price Prediction using ML" ICICACS International Conference on Integrated Circuits and Communication Systems, Scopus indexed, ISBN:979-8-3503-1755-8/ https://ieeexplore.ieee.org/document/10498248,18 April 2024

53. B.Aruna Kumari "HumanvAction Recognition From Video Frames Using Recurrent Neural Networks" ICDT 2nd International Conference on Disruptive Technologies (ICDT),Scopis indexed ,ISBN:979-8-3503-7105-5/ https://ieeexplore.ieee.org/document/10489658, 11 April 2024

54. Shamrat, F. J. M., Akter, S., Azam, S., Karim, A., Ghosh, P., Tasnim, Z., ... & Ahmed, K. (2023). Alzheimer Net: An effective deep learning-based proposition for Alzheimer's disease stages classification from functional brain changes in magnetic resonance images. IEEE Access, 11, 16376-16395.

55. Fathi, S., Ahmadi, A., Dehnad, A., Almasi-Dooghaee, M., Sadegh, M., & Alzheimer's Disease Neuroimaging Initiative. (2024). A deep learning-based ensemble method for early diagnosis of Alzheimer's disease using MRI images. Neuroinformatics, 22(1), 89-105.

56. Helaly, H. A., Badawy, M., & Haikal, A. Y. (2022). Deep learning approach for early detection of Alzheimer's disease. Cognitive computation, 14(5), 1711-1727.