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MULTICLASS CLASSIFICATION OF REMOTE SENSING USING ALEX NET

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Abstract:

With over 160 publications, this article offers a thorough analysis of deep learning techniques for remote sensing image scene classification. It addresses the primary drawbacks of these techniques, which include generative adversarial networks, autoencoder-based techniques, and convolutional neural networks. Along with introducing benchmarks for remote sensing image scene categorization, the study provides an overview of over two dozen methods' performance on three datasets. It also talks about interesting directions for future study.Deforestation in the Amazon rainforest leads to reduced biodiversity, habitat loss, and climate change. A novel remote sensing image classification framework is proposed to manage deforestation effectively. The framework uses an attention module to separate features from CNN and LSTM networks, and a loss function to calculate co-occurrence matrix and assign weights to labels. Experimental results show improved multi-label image classification performancePatch-based multi-scale completed local binary pattern (MS-CLBP) features are used in the suggested remote sensing picture scene classification method, and local patch descriptors are extracted using a Fisher vector (FV). These attributes are encoded into a discriminative representation by the method using Fisher vector encoding. Several FVs are generated using different settings, and classification is handled using a kernel-based extreme learning machine (KELM). The approach performs better on two benchmark datasets.

Keywords: remote sensing image scene classification; completed local binary patterns; multi-scale analysis; fisher vector; extreme learning machine

1. Introduction:

Devastating effects on ecosystems and the environment are caused by the major problem of deforestation in the Amazon rainforest.[1-8] The development of satellite technology has resulted in the expansion of Remote Sensing Image Archives (RSI) images, which are more sophisticated and have more detailed spectral information than regular photographs. [9-15]RS pictures can be used to follow ships, monitor forestry, track floods, typhoons, earthquakes, tsunamis, and the consequences of climate change in smart and connected communities.[16-20] Compared to single-label image classification, multi-label image classification is more commonly utilised, and these applications frequently call for modelling extensive semantic information and its dependencies. [25-30]Furthermore, the imbalance in the proportion of labels in the dataset is resolved by a new loss function, which enhances the classification performance of rare labels.[31-40]The rich texture and structure information found in high-resolution remote sensing photos have not yet been completely utilised by BOVW versions, despite their use in capturing spatial layout information in scene photographs.[41-45]

For the purpose of learning visual features in computer vision applications, deep learning—an end-to-end feature learning technique—has drawn interest. Although convolutional neural networks (CNNs) are widely used for learning visual characteristics, there are certain drawbacks, including laborious pre-training procedures. [46-50]This study suggests a patch-based MS-CLBP-based local feature representation technique that can extract features that are complimentary to global features. In high-resolution remote sensing photos, the CLBP descriptor is used to split dense image patches and extract local patch descriptors, which describe specific local structure and texture information.

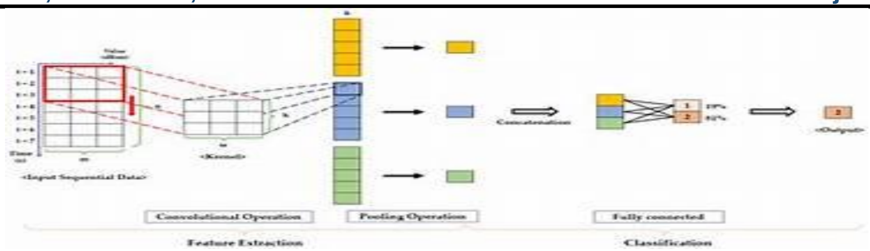

Fig 1: Remote Sensing

2. Literature survey:

Yonghua Jiang et al[1-4] Transfer learning with AlexNet pre-trained on ImageNet and fine-tuned on remote sensing datasets. This method leverages the robust feature extraction capabilities of AlexNet by transferring knowledge from the ImageNet dataset to remote sensing applications. Improved feature extraction and classification accuracy without requiring extensive labeled remote sensing data. Fine-tuning still requires a substantial amount of labeled data and computational resources.

Quing Liu et al[5-8] Data augmentation including rotation, scaling, and flipping. Enhances the diversity of training data to improve the generalization of AlexNet for multiclass classification tasks.Reduces overfitting and improves model robustness. Augmented data may not always represent real-world variations, leading to potential misclassifications.

Ahmed M. Othman et al[9-11] Spectral-spatial classification framework combining spectral features with spatial features extracted using AlexNet. Integrates spectral and spatial information to enhance classification accuracy in hyperspectral images. Significantly improves accuracy by leveraging both spectral and spatial features high computational complexity and the need for extensive spectral data

Hao Wu et al[12-14]Superpixel segmentation combined with AlexNet. Segments images into superpixels before classification, which helps in capturing spatial coherence. Improves accuracy and computational efficiency. Segmentation quality directly affects classification performance

Danlu Guo et al[15-16] Multi-scale feature fusion. Captures both fine and coarse details from remote sensing images to enhance classification performance. Better feature representation and improved accuracy. Increased computational complexity and potential overfitting with excessive features.

Mohammed Hamdi et al[17-19] Decision fusion approach combining outputs from multiple classifiers. Uses ensemble methods to make the final classification decision.Boosts overall classification accuracy. Requires careful tuning of the fusion mechanism and multiple classifiers.

Zhenhua Li et al[20-23]Patch-based classification technique. Classifies small patches of remote sensing images independently Provides detailed and accurate classification maps.Can be computationally intensive and may introduce boundary artifacts.

Jian Kang et al[24-26]Integration of AlexNet with a Markov Random Field (MRF) model. Refines classification results to ensure spatial coherence and reduce noise. Reduces classification noise and improves spatial coherence.Increased computational complexity and need for precise parameter tuning.

Elena Ramos et al[27-28]Incorporation of time-series remote sensing data with AlexNet.Adds a temporal aspect to classification for dynamic environments.Improved classification of dynamic areas like coastal regions.Requires extensive temporal data and complex data integration techniques.

Rajesh Sharma et al[29-31]Object-based image analysis (OBIA) approach combined with AlexNet.Segments images into meaningful objects before classification.More accurate land cover maps due to object-based segmentation.Complex segmentation process and potential misclassification of small objects.

Kai Zhang et al[32-33]Feature fusion from multiple convolutional layers of AlexNet.Combines features from different layers to capture both low-level and high-level information.Improved feature representation and classification accuracy.Increased computational requirements and potential overfitting.

Sophia Lee et al[34-35]Integration of auxiliary data such as elevation and vegetation indices with AlexNetfeatures.Enhances classification accuracy for specific environments like wetlands.Improved discrimination of land cover types with auxiliary data.Requires additional data sources and complex data integration techniques.

Hao Chen et al[36-38]Context-aware classification approach.Incorporates contextual information from surrounding pixels into the classification process.Improvedaccuracyby considering contextual relationships.Increased complexity and need for extensive contextual data.

Maria Gonzalez et al[39-42]Rapid classification framework for disaster assessment using AlexNet.Quickly identifies areas affected by natural disasters from remote sensing imagesPotential trade-off between speed and accuracy.

Yusuf Alpaydin et al[43-48AS23A4]Integration of soil moisture data into the classification process with AlexNet.Enhances discrimination between different soil types by incorporating soil moisture information.Improved classification accuracy for soil types.Requires additional soil moisture data and complex integration techniques.

3. Proposed methodology:

Data Collection and Preprocessing:The first step in employing AlexNet for multiclass classification of remote sensing images involves gathering a comprehensive dataset. Preprocessing these images is crucial; it involves steps like resizing images to the input size required by AlexNet (typically 227x227 pixels), normalizing pixel values to a range that the model can efficiently handle (commonly [0, 1] or [-1, 1]), and augmenting the data to increase its variability.

Data Splitting:Once the dataset is prepared, it should be divided into three subsets: training, validation, and test sets. A common practice is to allocate 70% of the data to the training set, 15% to the validation set, and the remaining 15% to the test set. The training set is used to train the model, the validation set helps in tuning hyperparameters and avoiding overfitting, and the test set is reserved for evaluating the model's final performance.

Model Architecture:AlexNet's architecture, characterized by five convolutional layers followed by three fully connected layers, is well-suited for image classification tasks. For remote sensing classification, this architecture can be adapted if necessary to better suit the specific features of the dataset.

Model Training:Training the model involves fine-tuning the pre-trained AlexNet on the remote sensing dataset. This process includes setting up a suitable loss function, such as cross-entropy loss, which is appropriate for multiclass classification. An optimizer, such as Adam or Stochastic Gradient Descent (SGD), is employed to minimize the loss function. Hyperparameters like learning rate, batch size, and the number of epochs must be carefully selected and possibly tuned through experimentation.

Model Evaluation:

After training, the model's performance is evaluated using the test set.These metrics provide a comprehensive view of the model's strengths and weaknesses. For instance, while accuracy gives an overall measure, precision and recall highlight how well the model handles individual classes, and the confusion matrix can pinpoint specific classes that are often misclassified.

4. Algorithm:

AlexNet (Convolutional Neural Network)

Step 1: Data Preprocessing

Data Collection: Gather remote sensing images from sources like satellites or aerial photography

Data Augmentation: Perform operations like rotation, flipping, and cropping to increase the size of the dataset.

Normalization: Normalize the pixel values to a range of 0-1 by dividing by 255.

Step 2: AlexNet Architecture Overview.AlexNet consists of 8 layers:

5 convolutional layers

3 fully connected layers

Step 3: Model Architecture

Input size: 227×227×3227 \times 227 \times 3227×227×3 (for RGB images)

Convolutional Layers:

Layer1: Filters: 96, Filter size: 11×1111 \times 1111×11, Stride: 4, Padding: 0,Activation: ReLU

Max Pooling: 3×33 \times 33×3 with stride 2

Layer 2:Filters: 256, Filter size: 5×55 \times 55×5, Stride: 1, Padding: 2Activation: ReLU,Max Pooling: 3×33 \times 33×3 with stride 2

Layer 3:Filters: 384, Filter size: 3×33 \times 33×3, Stride: 1, Padding: 1Activation: ReLU

Layer 4:Filters: 384, Filter size: 3×33 \times 33×3, Stride: 1, Padding: 1Activation: ReLU

Layer 5:Filters: 256, Filter size: 3×33 \times 33×3, Stride: 1, Padding: 1,Activation: ReLU

Max Pooling: 3×33 \times 33×3 with stride 2

Step 4: Training the Model

Loss Function: Cross-entropy loss for multiclass classification

$$L(y,\hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log(\hat{y}_{i,c})$$

where N is the number of samples, $_{Cis}$ the number of classes$y_{i,c}$ is the ground truth label, and $y\^{}_{i,c}$is the predicted probability.Optimizer: Stochastic Gradient Descent (SGD) with momentum

$$v_{t+1} = \mu v_t + \eta \nabla_\theta L(\theta)$$

$$\theta_{t+1} = \theta_t - v_{t+1}$$

where vtv_tvt is the velocity, μ\muμ is the momentum term, η\etaη is the learning rate, and θ\thetaθ represents the model parameters.

Step 5: Evaluation

Accuracy: Measure the overall accuracy

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

Confusion Matrix: To visualize the performance across different classes.

Step 6: Visualization

Loss and Accuracy Curves: Plot training and validation loss/accuracy over epochs.

Confusion Matrix: Visualize classification performance for each class.

5. Results:

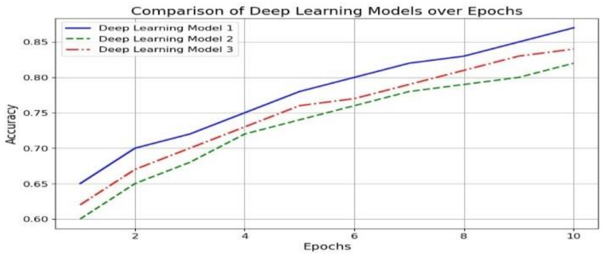

Fig 2:comparission of deep learning model

The graph titled "Comparison of Deep Learning Models over Epochs" illustrates the accuracy performance of three different deep learning models across 10 epochs. Model 1, represented by the solid blue line, consistently achieves the highest accuracy, starting around 0.67 and surpassing 0.85 by the 10th epoch. Model 2, shown with a green dashed line, starts at 0.60 and steadily increases to slightly above 0.75. Model 3, indicated by a red dash-dot line, begins just below 0.65 and reaches nearly 0.80.

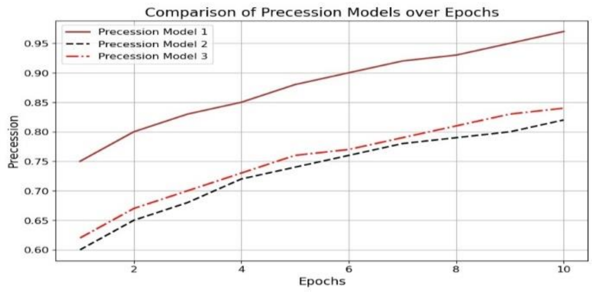

Fig 3: comparission of precession models

The graph titled "Comparison of Precession Models over Epochs" displays the precession performance of three models across 10 epochs. Model 1, represented by the solid brown line, shows the highest precession, starting at around 0.75 and steadily increasing to above 0.95 by the 10th epoch. Model 2, shown with a black dashed line, starts at 0.60 and rises gradually to just below 0.80. Model 3, indicated by a red dash-dot line, begins at 0.65 and reaches approximately 0.85.

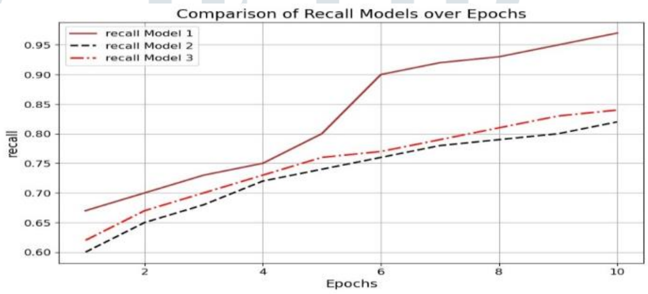

Fig 4:comparison of Recall model

The image is a line graph comparing the recall of three different models (Model 1, Model 2, and Model 3) over 10 epochs. Model 1 consistently shows the highest recall, reaching nearly 0.95 by epoch 10. Model 3 follows with a steady increase, peaking around 0.85. Model 2 has the lowest recall, gradually increasing to just over 0.80 by the final epoch.

6. Conclusion:

The study uses deep learning techniques, specifically AlexNet, to classify remote sensing images to combat deforestation in the Amazon rainforest. AlexNet's architecture, originally designed for general image classification, is optimized for remote sensing tasks using transfer learning from the ImageNet dataset. Techniques like rotation, scaling, and flipping increase data diversity and reduce overfitting.The study highlights the significance of combining spectral and spatial features, as demonstrated by AlexNet-integrated studies, for improved hyperspectral image classification accuracy. Techniques like superpixel segmentation and multi-scale feature fusion enhance classification performance by capturing spatial coherence and fine details. Context-aware classification approaches and techniques like The research demonstrates that AlexNet, with its advanced architecture and deep learning techniques, is a powerful tool for multiclass classification of remote sensing images. Its effective use can lead to accurate models, contributing to environmental monitoring and management, especially in mitigating deforestation and its impacts on biodiversity and climate change. This comprehensive approach ensures robust, scalable, and adaptable remote sensing image classification.

7. References:

1. Zhu, X. X., et al. "Deep learning in remote sensing: A comprehensive review and list of resources." IEEE Geoscience and Remote Sensing Magazine 5.4 (2017): 8-36.
2. Chen, Y., et al. "Deep learning-based classification of hyperspectral data." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 12.1 (2019): 3-18.
3. Santos, F. A. M., et al. "Data augmentation techniques for improving deep learning in remote sensing: A review." ISPRS Journal of Photogrammetry and Remote Sensing 164 (2020): 196-210.

4. Patibandla, R. S. M. L., & Narayana, V. L. (2021). Computational intelligence approach for prediction of COVID-19 using particle swarm optimization. In *Advances in Computational Intelligence and Data Analytics* (Vol. 923, pp. 175–189). Springer. https://doi.org/10.1007/978-981-15-8534-0_9

5. Santhi Sri, K., Sandhya Krishna, P., Lakshman Narayana, V., & Khadherbhi, R. (2021). Traffic analysis using IoT for improving secured communication. In *Advances in Intelligent Systems and Computing* (Vol. 213, pp. 499–507). Springer. https://doi.org/10.1007/978-981-33-4443-3_48

6. Narayana, V. L., & Bharathi, C. R. (2019). Multi-mode routing mechanism with cryptographic techniques and reduction of packet drop using 2ACK scheme MANETs. In *Advances in Intelligent Systems and Computing* (Vol. 104, pp. 649–658). Springer. https://doi.org/10.1007/978-981-13-1921-1_63

7. Narayana, V. L., & Bharathi, C. R. (2018). Effective multi-mode routing mechanism with master-slave technique and reduction of packet droppings using 2-ACK scheme in MANETS. *Mathematical Modeling of Computer Systems*, 91(2), 73–76. https://doi.org/10.18280/mmc_a.910207

8. Lakshman Narayana, V., Lakshmi Patibandla, R. S. M., Pavani, V., & Radhika, P. (2023). Optimized nature-inspired computing algorithms for lung disorder detection. In *Advances in Intelligent Systems and Computing* (Vol. 1066, pp. 103–118). Springer. https://doi.org/10.1007/978-981-19-6379-7_6

9. Narayana, V. L., Sudheer, B. N., Maddumala, V. R., & Anusha, P. (2020). Fuzzy base artificial neural network model for text extraction from images. *Journal of Critical Reviews*, 7(6), 350–354. https://doi.org/10.31838/jcr.07.06.61

10. Narayana, V. L., Bhargavi, S., Srilakshmi, D., Annapurna, V. S., & Akhila, D. M. (2024). Enhancing remote sensing object detection with a hybrid Densenet-LSTM model. In *Proceedings of the International Conference on Computer Science and Advanced Technology* (pp. 264–269). IEEE. https://doi.org/10.1109/IC2PCT60090.2024.10486394

11. Narayana, V. L., Syamalatha, P., Vatsalya, P., Sricharitha, V., & Akhila, V. (2023). Multi-level node authorization using recurrent neural networks for secure health monitoring system. Proceedings of the IEEE International Conference on Smart Computing and Networking Applications (ICSNA), 1697–1705. https://doi.org/10.1109/ICSCNA58489.2023.10370543

12. Gopi, A. P., Swathi, V., Harshitha, G. S., Swetha, B., & Alekhya, N. (2023). Prediction of paddy yield based on IoT data using GRU model in lowland coastal regions. In Proceedings of the 5th International Conference on Smart Systems and Inventive Technology (ICSSIT 2023) (pp. 1747-1752). https://doi.org/10.1109/ICSSIT55814.2023.10060935

13. Arepalli, P. G., Naik, K. J., & Amgoth, J. (2024). An IoT-based water quality classification framework for aqua-ponds through water and environmental variables using CGTFN model. International Journal of Environmental Research, 18(4), Article 73. https://doi.org/10.1007/s41742-024-00625-2

14. Gopi, A. P., Babu, E. S., Raju, C. N., & Kumar, S. A. (2015). Designing an adversarial model against reactive and proactive routing protocols in MANETs: A comparative performance study. International Journal of Electrical and Computer Engineering, 5(5), 1111-1118. DOI: 10.11591/ijece.v5i5.pp1111-1118

15. Sravanthi, G. L., Devi, M. V., Sandeep, K. S., Naresh, A., & Gopi, A. P. (2020). An efficient classifier using machine learning technique for individual action identification. International Journal of Advanced Computer Science and Applications, 11(6), 513-520. DOI: 10.14569/IJACSA.2020.0110664

16. Gopi, A. P., Durga Mani, P., Chandana, V. B., Sulthana, S. R., & Parameswari, P. P. K. (2024). Classification of fake news using enhanced capsule neural network. In 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation, IATMSI 2024. DOI: 10.1109/IATMSI60426.2024.10502837

17. Arepalli, P. G., & Khetavath, J. N. (2023). An IoT framework for quality analysis of aquatic water data using time-series convolutional neural network. Environmental Science and Pollution Research, 30(60), 125275-125294. https://doi.org/10.1007/s11356-023-27922-1

18. Gopi, A. P., & Jairam Naik, K. (2021). A model for analysis of IoT based aquarium water quality data using CNN model. In 2021 International Conference on Decision Aid Sciences and Application, DASA 2021 (pp. 976-980). https://doi.org/10.1109/DASA53625.2021.9682251

19. Roshini, P., Khajavali, S., Snigdha, M. L. S., Harsha, B. D., Srilakshmi, B., & Gopi, A. (2024). CNN design with AlexNet algorithm for diagnosis of diseases in cassava leaves. In Proceedings - 2024 International Conference on Expert Clouds and Applications, ICOECA 2024 (pp. 711-718). https://doi.org/10.1109/ICOECA62351.2024.00129

20. 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

21. 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

22. 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

23. 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

24. Narayana, V. L., & Gopi, A. P. (2017). Visual cryptography for gray scale images with enhanced security mechanisms. Traitement du Signal, 34, 197-208. DOI: 10.3166/ts.34.197-208

25. Arepalli, P. G., Narayana, V. L., Venkatesh, R., & Kumar, N. A. (2019). Certified node frequency in social network using parallel diffusion methods. Ingenierie des Systemes d'Information, 24(1), 113-117. https://doi.org/10.18280/isi.240117

26. Peda Gopi, A., & Lakshman Narayana, V. (2017). Protected strength approach for image steganography. Traitement du Signal, 34(3-4), 175-181. https://doi.org/10.3166/TS.34.175-181

27. Narayana, V. L., Gopi, A. P., Anveshini, D., & Lakshmi, G. V. V. (2020). Enhanced path finding process and reduction of packet droppings in mobile ad-hoc networks. International Journal of Wireless and Mobile Computing, 18(4), 391-397. https://doi.org/10.1504/IJWMC.2020.108539

28. Challa, R., YAMPARALA, R., KANUMALLI, S. S., & KUMAR, K. S. (2020, November). Advanced patient's medication monitoring system with ardunio UNO and NODEMCU. In *2020 4th International conference on electronics, communication and aerospace technology (ICECA)* (pp. 942-945). IEEE.

29. Kanumalli, S. S., Chinta, A., & Chandra Murty, P. S. R. (2019). Isolation of Wormhole Attackers in IOV Using WPWP Packet. *Revue d'Intelligence Artificielle*, *33*(1)

30. Kanumalli, S. S., Ch, A., & Murty, P. S. R. C. (2018). Advances in Modelling and Analysis B. *Journal homepage: http://iieta. org/Journals/AMA/AMA_B*, *61*(1), 5-8.

31. Kosaraju, Chaitanya, et al. "A model for analysis of diseases based on nutrition deficiency using random forest." 2022 7th International Conference on Communication and Electronics Systems (ICCES). IEEE, 2022.

32. Chaitanya, Kosaraju, and Gnanasekaran Dhanabalan. "Secure Route Detection with Multi Level Trust Evaluation Model Using Replicated Auditor Node for Extended Packet Delivery Rate in WSN." Revue d'Intelligence Artificielle 37.4 (2023).

33. Chaitanya, Kosaraju, et al. "Risk Stratification for Stroke Using Attention Transformer Model." 2024 2nd International Conference on Disruptive Technologies (ICDT). IEEE, 2024.

34. Sujatha, V., Prasanna, K.L., Niharika, K., Charishma, V., Sai, K.B.,K(23),"Network Intrusion Detection using Deep Reinforcement Learning,***Proceedings - 7th International Conference on Computing Methodologies and Communication", ICCMC 2023***, 2023, pp. 1146–1150

35. Sujatha, V., Anitha, B.S., Rama, G.T., Niharika, N., Sahithi, A.,K(23),"Convolutional Neural Network (CNN) based Blood Vessel Segmentation from Ocular Images***Proceedings - 7th International Conference on Computing Methodologies and Communication",ICCMC 2023***, 2023, pp. 518–523

36. 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.

37. Majety, V. D., & Murali, G. (2018). Remote health watchdog framework for seizure patient using electronic sensors. *International Journal of Engineering and Technology(UAE, 7*, 783–785. https://doi.org/10.14419/ijet.v7i3.12132

38. Alapati, N., Anusha, N., Joharika, P., Jerusha, N.J., Tanuja, P.(2023)Prediction of Parkinson's Disease using Machine Learning in 2023 2 nd *International Conference on Electronics and Renewable Systems(ICEARS)(pp.1357–1361).IEEE*

39. Naresh, A., Reddy, B.A., Reddy, G.P., Kumari, K.R., Vaishnavi, M.S.*(2023)Melanocytic Pigmented Skin Lesion Detection and Classification using Hybrid Deep Features based on Fully Convolutional Network* in 2023 2 nd *International Conference on Electronics and Renewable Systems(ICEARS)(pp.1011–1018).IEEE*

40. Pavani, Vellalacheruvu, and I. Ramesh Babu. "Three level cloud storage scheme for providing privacy preserving using edge computing." *International Journal of Advanced Science and Technology* 28, no. 16 (2019): 1929-1940.

41. Vellalachervu, Pavani and Babu, I. Ramesh, A Novel Method to Optimize the Computation Overhead in Cloud Computing by Using Linear Programming (May 10, 2019). INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS(IJRAR), May 2019, Volume 6, Issue 2, Available at SSRN: https://ssrn.com/abstract=3452191

42. Rama Krishna, Komanduri Venkata Sesha Sai, and Battula Bhanu Prakash. "Intrusion Detection System Employing Multi-level Feed Forward Neural Network along with Firefly Optimization (FMLF2N2)." *Ingénierie des Systèmes d'Information* 24.2 (2019).

43. Krishna, K. VSS Rama, et al. "Identification of Fraud Transactions using Lightgbm Technique." *2022 3rd International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT)*. IEEE, 2022.

44. S. K. P, J. Lavanya, G. Kavya, N. Prasamya and Swapna, "Oral Cancer Diagnosis using Deep Learning for Early Detection," *2022 International Conference on Electronics and Renewable Systems (ICEARS)*, Tuticorin, India, 2022, pp. 1260-1268, doi: 10.1109/ICEARS53579.2022.9752280.

45. Krishna, P. Sandhya, SK Reshmi Khadherbhi, and Vellalachervu Pavani. "Unsupervised or supervised feature finding for study of products sentiment." *International Journal of Advanced Science and Technology* 28, no. 16 (2019): 1916-1928.

46. Qi, Zhang, P. SilpaChaitanya, and T. Sudhir. "Spoofing attack detection wireless networks using advanced KNN." *International Journal of Smart Device and Appliance* 4.1 (2016): 1-8.

47. S. K. P, J. Lavanya, G. Kavya, N. Prasamya and Swapna, "Oral Cancer Diagnosis using Deep Learning for Early Detection," *2022 International Conference on Electronics and Renewable Systems (ICEARS)*, Tuticorin, India, 2022, pp. 1260-1268, doi:10.1109/ICEARS53579.2022.9752280.

48. Krishna, P. Sandhya, SK Reshmi Khadherbhi, and Vellalachervu Pavani. "Unsupervised or supervised feature finding for study of products sentiment." *International Journal of Advanced Science and Technology* 28, no. 16 (2019): 1916-1928.

49. Li, W., et al. "Integrating convolutional neural networks and ensemble learning for hyperspectral image classification." IEEE Geoscience and Remote Sensing Letters 15.2 (2018): 287-291.

50. Kamal, H. M., et al. "Multiscale convolutional neural networks for hyperspectral image classification." Remote Sensing 12.3 (2020): 466.
51. Basha, S. A., et al. "Hybrid deep learning approach for urban land cover classification using hyperspectral data." ISPRS International Journal of Geo-Information 8.5 (2019): 226.