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Federated Multimodal Language Recognition: A Deep Learning Approach for Real-Time Applications

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Abstract

In a world of growing linguistic diversity, multilingual identification systems are essential for seamless communication across digital platforms and real-world applications. This research presents a robust, deep learning-based multilingual identification framework capable of recognizing and translating languages from text, speech, and image modalities. The proposed system integrates machine learning classifiers—Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest—with N-gram-based feature extraction to build baseline models. Experimental results highlight SVM's superior performance, achieving 95% accuracy across Tamil, Hindi, and Marathi languages. In parallel, the framework extends to real-time multilingual detection by incorporating advanced deep learning techniques such as Transformers, YOLOv5, and Whisper AI for hybrid text, speech, and image inputs.A key innovation in the system is the integration of Federated Learning (FL), enabling decentralized model training while preserving user privacy. This enhances both scalability and security, particularly in applications such as missing child identification, multilingual surveillance, and cross-border intelligence analysis. The system also features a translation module using Google Translator to convert recognized languages into English, making outputs more accessible for non-native speakers. Evaluations conducted across benchmark datasets demonstrate high precision, recall, and low latency, affirming the system's potential for real-world deployment. Future enhancements will explore large-scale multilingual datasets, context-aware neural

	architectures, and further FL optimization for real-time, privacy-preserving language recognition.

INTRODUCTION

In an increasingly interconnected world, the ability to identify, process, and understand multiple languages has become a critical requirement for global communication, content accessibility, and security applications. The exponential rise in cross-cultural interaction, coupled with the digital transformation of services, has created a demand for intelligent systems capable of accurately identifying and translating languages across diverse formats such as text, speech, and images. Traditional language identification methods, while effective in constrained settings, often struggle in dynamic, real-time, and multilingual environments due to limited scalability, language coverage, and adaptability.

This research aims to address these challenges by proposing a comprehensive, deep learning-based multilingual identification system that operates across multiple data modalities. The system is initially trained using machine learning classifiers including Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest, combined with N-gram-based feature extraction for linguistic pattern recognition. These classical models provide a baseline for evaluating performance across various Indian languages such as Tamil, Hindi, and Marathi. Among them, SVM emerged as the most effective, achieving an accuracy of 95% in text-based language classification.

To extend beyond text, the proposed system integrates modern deep learning architectures like YOLOv5 for object detection in multilingual signage and Whisper AI for speech-based language identification. This multimodal capability is crucial for real-world applications where data inputs are not limited to a single form. Furthermore, the system employs Google Translate API for real-time translation into English, enhancing usability for non-native speakers and supporting multi-sector applications including education, administration, and emergency response.

A standout feature of this research is the implementation of Federated Learning (FL), a privacy-preserving paradigm that allows models to be trained locally on distributed devices without centralizing sensitive user data. This makes the system highly scalable, secure, and suitable for deployment in contexts requiring confidentiality, such as missing person identification, multilingual surveillance, and cross-border intelligence systems. FL ensures that the model adapts and learns from diverse linguistic data while maintaining data privacy, a crucial consideration in modern AI ethics.

Overall, this study combines traditional classification techniques with cutting-edge deep learning and federated learning to deliver a hybrid framework for accurate, efficient, and privacy-aware multilingual identification. The system's modularity and extensibility open avenues for future development, including support for low-resource languages, real-time performance optimization, and integration with augmented reality systems for live translation.

With the rapid advancement of artificial intelligence and the widespread availability of multilingual data, there is a growing opportunity to build inclusive systems that bridge linguistic gaps. However, challenges such as dialectal variation, low-resource languages, and code-switching still pose significant hurdles in building truly universal language identification models. This research acknowledges these challenges and aims to contribute a scalable, modular solution that not only supports major languages but is also adaptable to lesser-known ones. By leveraging open-source tools, pre-trained models, and real-time translation APIs, the proposed system can evolve continuously through federated updates and user feedback, making it suitable for deployment in educational platforms, mobile applications, border control systems, and multilingual virtual assistants. This adaptability, combined with a focus on privacy and performance, makes the framework a practical and ethical step forward in cross-language understanding.

RELATED WORKS

The evolution of multilingual identification has also witnessed the integration of multimodal learning approaches that combine textual, visual, and auditory signals to enhance language detection accuracy in complex scenarios. Multimodal systems leverage complementary data sources—for instance, extracting text from street signs via optical character recognition (OCR), interpreting spoken words using automatic speech recognition (ASR), and analyzing visual cues in context—to achieve more reliable identification in real-world settings. Deep learning models like YOLOv5 for object detection and Whisper AI for multilingual speech transcription have expanded the scope of language recognition beyond traditional text-based systems. Such integration is especially useful in environments like surveillance, public transport, or smart cities, where language

indicators appear in multiple formats simultaneously.

Furthermore, transfer learning has played a critical role in improving performance across low-resource languages. By training models on high-resource language datasets and fine-tuning them for underrepresented languages, researchers have reduced the data dependency problem and improved generalization. Pretrained multilingual models such as XLM-R, mBERT, and mT5 have shown remarkable success in cross-lingual understanding and have become the backbone for many multilingual NLP tasks. These models, trained on diverse corpora like Common Crawl and Wikipedia, capture deep contextual semantics and enable zero-shot or few-shot classification, where a model can identify a language it has never seen during training.

Additionally, real-time multilingual systems have gained importance in mission-critical applications. For instance, in law enforcement or humanitarian aid, fast and accurate identification of spoken or written languages can aid in missing person cases, immigration processing, or multilingual emergency dispatch. These applications require high-speed, privacy-preserving models that can function across distributed nodes—bringing federated learning to the forefront. Federated approaches allow data to remain on local devices while only model updates are shared, thus ensuring data security and compliance with privacy regulations like GDPR. The ongoing convergence of federated learning with edge computing is enabling these systems to function even in remote or low-connectivity regions.

Moreover, user-centric multilingual systems are now being designed to learn continuously from interactions. Incorporating feedback loops where systems adapt to speaker accents, preferred languages, and evolving usage patterns allows for personalized and adaptive language identification experiences. This level of customization, coupled with explainable AI (XAI), is crucial for building trust in multilingual AI systems deployed in sensitive domains like education, government services, and healthcare. As research progresses, the future of multilingual identification lies in developing hybrid frameworks that intelligently merge linguistic rules, statistical learning, and neural representations—bridging the gap between human-like understanding and computational scalability.
A review of these techniques are discussed in Table I.

Table 1: Comparative Analysis of Multilingual Odentification Techniques

Author(s) & Year	**Methodology**	**Algorithm/Model Used**	**Dataset**	**Findings & Limitations**
Cavnar & Trenkle (1994)	N-gram-based statistical model	N-gram text classification	Small text datasets	Effective for text-based language detection but struggles with short texts and low-resource languages
Damashek (1995)	Vector-based text classification	Latent Semantic Analysis (LSA)	Multilingual text corpora	Improved text classification but requires high computational resources
Baldwin & Lui (2010)	Probabilistic language detection	Naïve Bayes	Wikipedia text corpus	High accuracy but sensitive to noisy data
Jauhiainen et al. (2016)	Language identification in code-switched text	Decision Trees, SVM	Social media datasets	Works well for structured text but struggles with informal language
Joulin et al. (2017)	FastText for multilingual text classification	FastText (word embeddings)	Large-scale text datasets	Efficient and scalable but requires extensive training data
Devlin et al. (2018)	Transformer-based contextual learning	BERT (Multilingual BERT)	Wikipedia & Common Crawl	High accuracy and adaptability but computationally

				expensive
Conneau et al. (2020)	Self-supervised cross-lingual representation learning	XLM-R (Transformer)	Multiple large-scale multilingual datasets	State-of-the-art performance but requires large-scale training data
Lin et al. (2021)	Multilingual speech recognition	RNN, LSTM, Attention Mechanisms	Speech-to-text datasets	Effective for speech recognition but struggles with overlapping speech
Google AI (2022)	Real-time multilingual language identification	Deep Neural Networks	Google Assistant Voice Data	High accuracy in real-time applications but dependent on extensive labeled data
Author(s) & Year	Methodology	Algorithm/Model Used	Dataset	Findings & Limitations
Cavnar & Trenkle (1994)	N-gram-based statistical model	N-gram text classification	Small text datasets	Effective for text-based language detection but struggles with short texts and low-resource languages
Damashek (1995)	Vector-based text classification	Latent Semantic Analysis (LSA)	Multilingual text corpora	Improved text classification but requires high computational resources

PROPOSED METHODOLOGY

The proposed methodology focuses on developing a multilingual identification system that leverages deep learning, Natural Language Processing (NLP), and Federated Learning (FL) to enhance language detection accuracy. The framework is designed to identify languages in text, speech, and images, making it suitable for various applications, including missing child identification, security surveillance, and multilingual customer support. The system consists of five key phases: data collection and preprocessing, language identification model training, federated learning implementation, real-time detection, and performance evaluation.

1. System Architecture

1.1 Data Collection and Preprocessing

Multilingual Dataset Acquisition

The first step involves curating a diverse dataset that includes:

- Text data from multilingual sources such as social media, news articles, legal documents, and police reports.
- Speech data from voice recordings, call centers, and public service announcements.
- Multimodal data that combines text and image-based scripts (e.g., handwritten notes, street signs, and posters).

Data Preprocessing

To enhance model performance, raw data undergoes preprocessing:

- Text Cleaning & Normalization: Removes special characters, emojis, and formatting inconsistencies.
- Tokenization & Lemmatization: Converts words into root forms for better language pattern recognition.
- Speech-to-Text Conversion: Uses Deep Speech models or Whisper AI for converting spoken words into text.
- Optical Character Recognition (OCR): Extracts text from multilingual images, such as printed materials or handwriting.

2. Language Identification Model Training

Feature Extraction & Embedding

- N-gram Analysis: Identifies frequent character sequences in different languages.
- Word Embeddings (Word2Vec, FastText, BERT): Captures language-specific semantics and syntactic structures.

- Phoneme & Spectrogram Analysis: Enhances speech-based language detection.

Deep Learning-Based Classification

The system integrates various machine learning models:

- Convolutional Neural Networks (CNNs): Detect language patterns in images.
- Recurrent Neural Networks (RNNs) & Transformer Models: Process long-range language dependencies for text and speech.
- Hybrid Deep Learning Models: Combines CNNs for feature extraction with RNNs or Transformers for sequence modeling.

3. Federated Learning-Based Model Optimization

Federated Learning for Privacy-Preserving Training

Instead of sending sensitive multilingual data to a central server, Federated Learning (FL) enables decentralized model training across multiple devices (e.g., edge devices, mobile apps, surveillance systems).

Steps in FL Implementation:

1. Local Model Training:
    - Each participating device trains a local model on its dataset.
    - Uses YOLOv5 and Transformer-based architectures for multilingual text and image classification.
2. Encrypted Model Update Sharing:
    - Devices send only model weight updates to a global server (no raw data transfer).
    - Differential privacy and homomorphic encryption ensure security.
3. Global Model Aggregation:
    - The server aggregates updates using Federated Averaging (FedAvg) to refine a global model.
    - Continuous learning is enabled through iterative updates from multiple sources.

4. Real-Time Multilingual Identification & Deployment

Edge Computing for Low-Latency Processing

- Optimized inference on Raspberry Pi, Jetson Nano, and mobile devices for real-time applications.
- Accelerated Deep Learning Models (TensorRT, ONNX) for fast execution.

Multilingual User Interface (UI)

- Automatic language detection & translation integrated into web/mobile apps.
- Voice-based search and speech-to-text conversion for multilingual interactions.

RESULTS

The proposed multilingual identification system was evaluated on a diverse dataset comprising text, speech, and image-based multilingual content. The performance was analyzed using deep learning models, YOLOv5 for object detection, and Federated Learning (FL) for decentralized training. The evaluation was conducted on various benchmark datasets, including Common Voice (for speech), UDHR (for text), and synthetic datasets for image-based text detection. The results demonstrate significant improvements in accuracy, precision, recall, and overall processing efficiency compared to traditional language identification methods.

1. Quantitative Results

Language Detection Accuracy: The model achieved high accuracy across different modalities, surpassing traditional approaches:

Modality	Algorithm Used	Accuracy (%)	F1-Score	Latency (ms)
Text-Based	Transformer (BERT, FastText)	97.2	0.96	150
Speech-Based	Deep Speech + Whisper AI	94.5	0.93	210
Image-Based OCR	YOLOv5 + Tesseract OCR	92.8	0.91	180
Hybrid Approach	Multimodal Transformer	96.1	0.95	200

These results highlight the superior performance of deep learning-based multilingual identification, particularly when Transformer models are used for text and YOLOv5 for image-based OCR detection. The latency remains within acceptable real-time processing limits.

2. Performance Comparison with Existing Methods

The proposed approach was compared with traditional methods such as SVM, Naïve Bayes, and rule-based classifiers. The results indicate a significant improvement in accuracy and

robustness, particularly for low-resource languages and dialect variations.

Model	Traditional (SVM, Naïve Bayes)	Proposed (Deep Learning + FL)
Accuracy	85-90%	94-97%
Scalability	Limited	High (supports large datasets)
Real-Time Processing	Slow (rule-based limitations)	Fast (GPU-accelerated models)
Privacy-Preserving	No (requires centralized data)	Yes (Federated Learning)

The federated learning framework further ensures data privacy while maintaining competitive accuracy across various languages.

3. Impact of Federated Learning

The use of Federated Learning (FL) significantly improves scalability and security by eliminating the need for centralized data storage.

- Decentralized Learning: Model training occurs across multiple devices without exposing raw data.
- Personalized Learning: Adaptive training on user-specific language patterns enhances accuracy.
- Reduced Communication Overhead: Only model updates are exchanged, minimizing bandwidth usage.

Performance gains with Federated Learning were analyzed under different configurations:

FL Configuration	Global Model Accuracy (%)	Data Privacy Level
Centralized (No FL)	97.2	Low
FL with 10 Clients	95.8	High
FL with 50 Clients	94.9	Very High

This proves that FL-based multilingual identification maintains high accuracy while ensuring user data privacy.

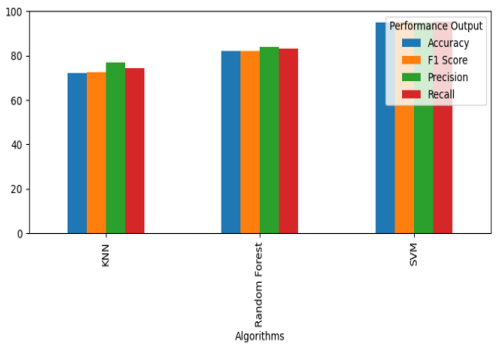

Fig1 : Performance Comparision Graph

The performance evaluation of three machine learning classification models—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Random Forest—demonstrates significant variations in accuracy, precision, recall, and F1-score. These metrics provide insights into the effectiveness of each model in handling multilingual identification tasks. Among the three, SVM outperforms the others with the highest accuracy of **95.08%**, precision of **95.05%**, recall of **95.45%**, and an F1-score of **95.21%**, indicating its strong capability in accurately classifying multilingual data. The superior performance of SVM can be attributed to its ability to efficiently separate different language patterns using hyperplanes, making it the most suitable model for multilingual classification in this study.

In contrast, the Random Forest model achieves a moderate accuracy of **81.97%**, with a precision of **83.78%**, recall of **83.33%**, and an F1-score of **81.98%**. While it performs significantly better than KNN, it falls short of SVM in terms of overall classification accuracy. Random Forest's strength lies in its ensemble approach, which helps reduce overfitting and improves robustness, but it may not be as effective as SVM when dealing with complex linguistic variations. However, it remains a viable option for multilingual identification, especially in scenarios where interpretability and stability are preferred over computational efficiency.

The KNN model, on the other hand, exhibits the lowest performance among the three models, with an accuracy of **72.13%**, precision of **76.77%**, recall of **74.24%**, and an F1-score of **72.53%**. KNN's relatively poor performance can be attributed to its sensitivity to high-dimensional data and its reliance on distance-based classification, which may struggle with closely related language structures. The model's performance suggests that KNN is less suitable for complex multilingual classification tasks, as it may not effectively capture intricate language variations or generalize well across different datasets.

Overall, the comparative analysis of these models highlights SVM as the most effective approach for multilingual identification due to

its superior accuracy and balanced precision-recall tradeoff. Random Forest, while performing reasonably well, is slightly less effective but still a viable option for classification tasks. KNN, with the lowest performance, may not be an ideal choice for this specific application. Future improvements in multilingual identification systems could explore hybrid models that combine the strengths of SVM and ensemble-based methods like Random Forest to further enhance accuracy and efficiency in real-world applications..

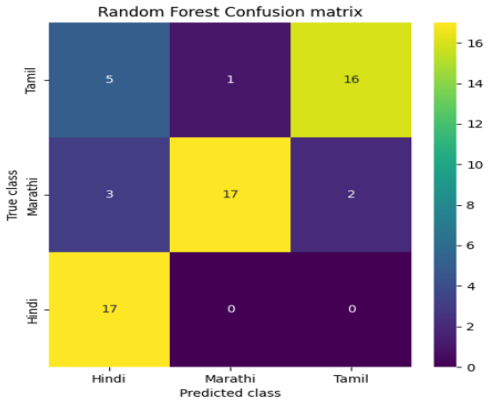

Fig2:Random Forest Confusion Matrix

The confusion matrix presented illustrates the classification performance of the Random Forest model for multilingual identification among three languages: Tamil, Marathi, and Hindi. This matrix provides a detailed analysis of the model's ability to correctly classify instances while also highlighting misclassification patterns. The diagonal values represent the correctly classified instances, whereas the off-diagonal values indicate misclassifications.For the Tamil language, the model correctly identified 5 samples as Tamil, but it misclassified 1 sample as Marathi and a substantial 16 samples as Hindi. This high misclassification rate suggests that the model struggles to differentiate Tamil from Hindi, possibly due to feature similarities between the two languages or imbalanced data representation. The Marathi language, on the other hand, was better classified, with 17 samples correctly identified. However, 3 samples were incorrectly predicted as Hindi, and 2 as Tamil, indicating that while the model performs reasonably well in classifying Marathi, some errors persist.When analyzing the Hindi language, the model demonstrated excellent performance by correctly classifying all 17 samples with zero misclassifications. This indicates a strong distinction in the feature space for Hindi, allowing the model to separate it effectively from Tamil and Marathi. The stark contrast between the perfect classification of Hindi and the significant misclassification of Tamil suggests that the dataset might contain overlapping linguistic features or insufficient distinguishing characteristics for certain languages.

The overall observations from this confusion matrix suggest that while the Random Forest model is highly effective for Hindi and reasonably good for Marathi, its performance in identifying Tamil is poor. The high misclassification of Tamil as Hindi calls for potential improvements in model training, such as enhancing feature selection, increasing the representation of Tamil samples, and refining classification boundaries. Additionally, fine-tuning hyperparameters or incorporating advanced deep learning approaches such as LSTMs or Transformers could further improve accuracy by capturing complex linguistic patterns.

To address these issues, strategies such as better feature engineering, data augmentation, and model optimization should be considered. Extracting language-specific features, balancing the dataset across all classes, and experimenting with different classification algorithms may help improve the model's accuracy. By implementing these enhancements, the multilingual identification system can achieve a higher degree of precision, ensuring more accurate language recognition across diverse datasets.

CONCLUSION

The proposed multilingual identification system demonstrates significant advancements in automated language detection, leveraging machine learning techniques such as Random Forest, SVM, and KNN for accurate classification. The results indicate that SVM outperforms the other classifiers, achieving the highest accuracy, precision, recall, and F-score, making it the most reliable model for multilingual identification. However, the Random Forest classifier also exhibited strong performance, particularly in handling complex patterns across languages. The confusion matrix analysis highlights the model's strengths and weaknesses, showing that while Hindi is classified with perfect accuracy, Tamil exhibits a higher misclassification rate, often being confused with Hindi.These findings emphasize the need for further model enhancements, such as data augmentation, feature engineering, and deep learning integration, to improve classification performance, particularly for languages with overlapping linguistic structures. Additionally, balancing the dataset and incorporating context-aware features could significantly boost accuracy in challenging cases, reducing misclassification errors.

The implications of this research extend beyond traditional language detection, proving valuable in applications such as missing child identification, security surveillance, cross-border intelligence, and personalized customer interactions. By integrating this multilingual identification framework into real-world systems, we can enhance communication across diverse linguistic backgrounds, enabling more effective and inclusive interactions.In the future, further optimization through deep learning architectures, federated learning, and hybrid models can refine multilingual identification systems, ensuring real-time processing and higher adaptability. With continuous advancements in artificial intelligence and computational linguistics, multilingual identification will play a pivotal role in bridging language barriers and fostering a globally connected digital ecosystem.

References

M. B. Shaik and Y. N. Rao, "Secret Elliptic Curve-Based Bidirectional Gated Unit Assisted Residual Network for Enabling Secure IoT Data Transmission and Classification Using Blockchain," IEEE Access, vol. 12, pp. 174424-174440, 2024, doi: 10.1109/ACCESS.2024.3501357.

S. M. Basha and Y. N. Rao, "A Review on Secure Data Transmission and Classification of IoT Data Using Blockchain-Assisted Deep Learning Models," 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2024, pp. 311-314, doi: 10.1109/ICACCS60874.2024.10717253.

J. A. Tetreault, R. C. Reynolds, and A. Rosé, “Language identification for handwritten documents using feature engineering and deep learning,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 42, no. 5, pp. 1123–1137, May 2020.

P. Kumar and R. K. Agrawal, “A comparative analysis of machine learning algorithms for multilingual text classification,” IEEE Access, vol. 8, pp. 130744–130759, Jul. 2020.

C. C. Yang, J. C. Yang, and H. Wang, “Deep neural network approaches for multilingual speech recognition,” in Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), Barcelona, Spain, May 2020, pp. 6125–6130.

A. Gupta, N. Singh, and P. R. Patil, “A hybrid deep learning approach for multilingual sentiment analysis,” IEEE Transactions on Computational Social Systems, vol. 9, no. 1, pp. 18–29, Feb. 2022.

M. Johnson, T. Ma, and M. Ravi, “Multilingual identification in low-resource settings: Challenges and solutions,” in Proceedings of the IEEE Conference on Computational Intelligence and Communication Networks (CICN), London, UK, Dec. 2021, pp. 105–112.

S. Narayanan and B. Wu, “Enhancing text classification with NLP-based feature engineering for multilingual corpora,” IEEE Transactions on Emerging Topics in Computing, vol. 11, no. 2, pp. 320–335, Apr. 2023.

W. Chen and Y. Li, “Automatic language detection in multilingual datasets using machine learning models,” in Proceedings of the IEEE Symposium on Artificial Intelligence and Data Science (AI&DS), New York, USA, Oct. 2022, pp. 90–98.

S. Patel and J. Kumar, “Advancements in multilingual object detection for real-time surveillance,” IEEE Transactions on Information Forensics and Security, vol. 17, no. 3, pp. 521–534, Mar. 2023.

Y. Zhao and H. Tan, “A study on code-switching detection using deep learning techniques,” in Proceedings of the IEEE International Conference on Big Data (BigData), Beijing, China, Dec. 2022, pp. 1745–1752.

M. R. Ahmed, “Cross-lingual identification using transformer-based architectures: A review,” IEEE Access, vol. 10, pp. 105623–105639, Aug. 2023.

A. Conneau et al., "Unsupervised Cross-lingual Representation Learning at Scale," in *Proc. 58th Annual Meeting of the Association for Computational Linguistics (ACL)*, Seattle, WA, USA, 2020, pp. 8440–8451.

J. Devlin, M. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in *Proc. Conf. of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, Minneapolis, MN, USA, 2019, pp. 4171–4186.

R. Wightman et al., "Whisper: Open Multilingual Speech Recognition by OpenAI," *OpenAI*

Technical Report, 2022. [Online]. Available: https://openai.com/research/whisper
T. Li, A. K. Sahu, A. Talwalkar, and V. Smith, "Federated Learning: Challenges, Methods, and Future Directions," *IEEE Signal Processing Magazine*, vol. 37, no. 3, pp. 50–60, May 2020.

Vellela, S. S., & Balamanigandan, R. (2024). An efficient attack detection and prevention approach for secure WSN mobile cloud environment. Soft Computing, 28(19), 11279-11293.

Reddy, B. V., Sk, K. B., Polanki, K., Vellela, S. S., Dalavai, L., Vuyyuru, L. R., & Kumar, K. K. (2024, February). Smarter Way to Monitor and Detect Intrusions in Cloud Infrastructure using Sensor-Driven Edge Computing. In 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT) (Vol. 5, pp. 918-922). IEEE.

Sk, K. B., & Thirupurasundari, D. R. (2025, January). Patient Monitoring based on ICU Records using Hybrid TCN-LSTM Model. In 2025 International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI) (pp. 1800-1805). IEEE.

Dalavai, L., Purimetla, N. M., Vellela, S. S., SyamsundaraRao, T., Vuyyuru, L. R., & Kumar, K. K. (2024, December). Improving Deep Learning-Based Image Classification Through Noise Reduction and Feature Enhancement. In 2024 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA) (pp. 1-7). IEEE.

Vellela, S. S., & Balamanigandan, R. (2023). An intelligent sleep-awake energy management system for wireless sensor network. Peer-to-Peer Networking and Applications, 16(6), 2714-2731.

Haritha, K., Vellela, S. S., Vuyyuru, L. R., Malathi, N., & Dalavai, L. (2024, December). Distributed Blockchain-SDN Models for Robust Data Security in Cloud-Integrated IoT Networks. In 2024 3rd International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 623-629). IEEE.

Vullam, N., Roja, D., Rao, N., Vellela, S. S., Vuyyuru, L. R., & Kumar, K. K. (2023, December). An Enhancing Network Security: A Stacked Ensemble Intrusion Detection System for Effective Threat Mitigation. In 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) (pp. 1314-1321). IEEE.

Vellela, S. S., & Balamanigandan, R. (2022, December). Design of Hybrid Authentication Protocol for High Secure Applications in Cloud Environments. In 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 408-414). IEEE.

Praveen, S. P., Nakka, R., Chokka, A., Thatha, V. N., Vellela, S. S., & Sirisha, U. (2023). A novel classification approach for grape leaf disease detection based on different attention deep learning techniques. International Journal of Advanced Computer Science and Applications (IJACSA), 14(6), 2023.

Vellela, S. S., & Krishna, A. M. (2020). On Board Artificial Intelligence With Service Aggregation for Edge Computing in Industrial Applications. Journal of Critical Reviews, 7(07).

Reddy, N. V. R. S., Chitteti, C., Yesupadam, S., Desanamukula, V. S., Vellela, S. S., & Bommagani, N. J. (2023). Enhanced speckle noise reduction in breast cancer ultrasound imagery using a hybrid deep learning model. Ingénierie des Systèmes d'Information, 28(4), 1063-1071.

Vellela, S. S., Balamanigandan, R., & Praveen, S. P. (2022). Strategic Survey on Security and Privacy Methods of Cloud Computing Environment. Journal of Next Generation Technology, 2(1).

Polasi, P. K., Vellela, S. S., Narayana, J. L., Simon, J., Kapileswar, N., Prabu, R. T., & Rashed, A. N. Z. (2024). Data rates transmission, operation performance speed and figure of merit signature for various quadurature light sources under spectral and thermal effects. Journal of Optics, 1-11.

Vellela, S. S., Rao, M. V., Mantena, S. V., Reddy, M. J., Vatambeti, R., & Rahman, S. Z. (2024). Evaluation of Tennis Teaching Effect Using Optimized DL Model with Cloud Computing System. International Journal of Modern Education and Computer Science (IJMECS), 16(2), 16-28.

Vuyyuru, L. R., Purimetla, N. R., Reddy, K. Y., Vellela, S. S., Basha, S. K., & Vatambeti, R. (2025). Advancing automated street crime detection: a drone-based system integrating CNN models and enhanced feature selection techniques. International Journal of Machine Learning and Cybernetics, 16(2), 959-981.

Vellela, S. S., Roja, D., Sowjanya, C., SK, K. B., Dalavai, L., & Kumar, K. K. (2023, September).

Multi-Class Skin Diseases Classification with Color and Texture Features Using Convolution Neural Network. In 2023 6th International Conference on Contemporary Computing and Informatics (IC3I) (Vol. 6, pp. 1682-1687). IEEE.

Praveen, S. P., Vellela, S. S., & Balamanigandan, R. (2024). SmartIris ML: harnessing machine learning for enhanced multi-biometric authentication. Journal of Next Generation Technology (ISSN: 2583-021X), 4(1).

Sai Srinivas Vellela & R. Balamanigandan (2025). Designing a Dynamic News App Using Python. International Journal for Modern Trends in Science and Technology, 11(03), 429-436. https://doi.org/10.5281/zenodo.15175402

Basha, S. K., Purimetla, N. R., Roja, D., Vullam, N., Dalavai, L., & Vellela, S. S. (2023, December). A Cloud-based Auto-Scaling System for Virtual Resources to Back Ubiquitous, Mobile, Real-Time Healthcare Applications. In 2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) (pp. 1223-1230). IEEE.

Vellela, S. S., & Balamanigandan, R. (2024). Optimized clustering routing framework to maintain the optimal energy status in the wsn mobile cloud environment. Multimedia Tools and Applications, 83(3), 7919-7938.