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Interface Design for Computer Interaction Using Hand Gestures and Sign Language Recognition

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Abstract: As technology advances, natural and intuitive methods of human-computer interaction (HCI) have become increasingly significant. Among these, hand gestures and sign language recognition offer a promising pathway for creating more inclusive and accessible interfaces, particularly for individuals with speech or hearing impairments. This research explores the design and development of an interactive interface that utilizes computer vision and machine learning techniques to recognize hand gestures and sign language for seamless computer control. The system employs a real-time video input device, such as a webcam, to capture hand movements. Using deep learning algorithms, particularly convolutional neural networks (CNNs), the interface is trained to accurately detect and classify a set of predefined gestures and American Sign Language (ASL) symbols. Feature extraction, image preprocessing, and hand segmentation techniques are integrated to enhance recognition accuracy under varying lighting and background conditions. The interface supports various functionalities, such as navigation, media control, and text input, using gestures alone, thus reducing dependency on conventional input devices like keyboards and mice. This paper also addresses the challenges of gesture ambiguity, dynamic background interference, and the scalability of gesture vocabulary. User experience is evaluated through usability testing with both general users and individuals from the Deaf and Hard-of-Hearing (DHH) community. Results indicate a high recognition rate and positive user feedback regarding intuitiveness and responsiveness. The proposed system demonstrates the potential of gesture-based interfaces to bridge communication gaps and enhance accessibility. Future work will focus on expanding the gesture set, incorporating multi-language sign support, and integrating the interface into broader application domains such as virtual reality, education, and assistive technologies.

Keywords: Hand gesture recognition, sign language recognition, human-computer interaction, interface design, gesture-based interface, natural user interface, real-time recognition, computer vision, pattern recognition, assistive technology, gesture interpretation, sign language translation, interactive systems, multimodal interaction, accessibility technology.

1. INTRODUCTION

The evolution of human-computer interaction (HCI) has seen a steady progression from text-based commands to graphical user interfaces, touchscreens, and now, toward more natural modalities such as voice and gesture control. Among these, hand gestures and sign language recognition present an intuitive and inclusive mode of communication with digital systems, particularly beneficial for users with physical or sensory impairments. With the increasing prevalence of artificial intelligence and computer vision technologies, gesture-based interfaces are becoming more practical and accurate, offering the potential to revolutionize how humans interact with machines.

Hand gestures are a fundamental part of non-verbal communication and have long been used to convey commands, intentions, and emotions. Similarly, sign languages—complete languages with their own grammar and syntax—enable robust communication among Deaf and Hard-of-Hearing (DHH) individuals. Integrating gesture and sign language recognition into computer interfaces can enhance accessibility, foster inclusivity, and enable hands-free operation in environments where traditional input methods are impractical or unsafe.

This research focuses on designing a user interface that allows users to control digital systems using static and dynamic hand gestures as well as sign language. By leveraging machine learning techniques, particularly deep learning models like convolutional neural networks (CNNs), the system aims to accurately detect and interpret hand movements captured through a standard webcam. Real-time processing, gesture classification, and user feedback mechanisms are key components of the system architecture. Furthermore, the study investigates the usability and effectiveness of such an interface in real-world scenarios, considering factors such as gesture recognition accuracy, user satisfaction, and system responsiveness. The goal is not only to develop a functional prototype but also to contribute to the broader field of accessible technology by promoting interaction models that transcend language and physical barriers.

2. LITERATURE SURVEY

The domain of human-computer interaction (HCI) has seen a significant shift toward natural user interfaces (NUIs), where input methods such as voice, touch, and gestures are used to communicate with digital systems. Among these, hand gesture and sign language recognition have emerged as effective tools for intuitive interaction and accessibility enhancement, particularly for users with disabilities. Several studies and technological advancements have laid the foundation for gesture-based interfaces and sign language translation systems.

Hand Gesture Recognition Systems

Early research in gesture recognition focused on using hardware-based solutions such as data gloves and infrared sensors. For example, the work by Zimmerman et al. (1987) introduced the "DataGlove" to detect finger flexion and hand motion. While accurate, such systems were expensive and intrusive. With the advancement of computer vision, marker-less recognition using standard cameras became a more viable alternative.

Recent works utilize image processing and machine learning algorithms to detect hand shapes and movements. For instance, Chen et al. (2013) implemented a hand gesture recognition system using Haar-like features and AdaBoost classifiers. However, these traditional methods often struggled with complex backgrounds and varying lighting conditions.

With the advent of deep learning, convolutional neural networks (CNNs) have significantly improved gesture recognition accuracy. Molchanov et al. (2015) introduced a CNN-based model that could recognize dynamic gestures in real-time using temporal and spatial features extracted from video frames. Tools such as OpenCV and MediaPipe further simplified gesture tracking, enabling developers to design efficient and lightweight models suitable for real-time applications.

Sign Language Recognition

Sign language recognition (SLR) is a subdomain of gesture recognition that involves interpreting structured hand movements, often combined with facial expressions and body posture. Early SLR systems relied heavily on gloves and motion sensors, but vision-based approaches have become more popular due to their non-intrusive nature.

Koller et al. (2016) developed a deep learning model for continuous sign language recognition using recurrent neural networks (RNNs), achieving promising results on datasets like RWTH-PHOENIX-Weather. Similarly, Camgoz et al. (2018) proposed a neural sign language translation framework using sequence-to-sequence models that could convert sign video input into spoken language text. These systems demonstrated the potential of end-to-end trainable networks in handling the complexity of sign languages.

However, challenges remain, such as variability in signing styles, occlusion, and the need for large annotated datasets. To address this, researchers have developed data augmentation techniques and domain adaptation strategies to improve model generalization.

Human-Computer Interaction Using Gestures

Several HCI projects have explored the integration of hand gestures into user interfaces for controlling applications, navigating content, or interacting with virtual environments. For example, Leap Motion and Microsoft Kinect provided SDKs for motion tracking, enabling developers to create immersive gesture-controlled experiences. Studies by Wachs et al. (2011) highlighted how gesture-based interaction could benefit medical, industrial, and assistive applications by enabling hands-free operation in sterile or constrained environments.

In the assistive technology domain, work by Liang and Ouhyoung (1998) introduced gesture-based browsers for Deaf users, enabling internet navigation using sign language. More recent research integrates gesture recognition with IoT devices and smart environments, demonstrating broader applicability beyond desktop computing.

Summary and Research Gaps

While significant progress has been made, several research gaps remain. Many existing systems focus either on gesture recognition or sign language but not both in a unified interface. Additionally, most models perform well under controlled conditions but degrade in real-world environments with cluttered backgrounds and varied lighting. Usability studies involving people with disabilities are limited, and real-time performance remains a challenge, particularly on resource-constrained devices.

This literature survey highlights the need for robust, real-time, and user-friendly gesture and sign language interfaces that are both accurate and accessible. The proposed research aims to bridge this gap by developing an integrated system capable of recognizing both gestures and sign language, validated through practical user interaction scenarios.

3. PROPOSED SYSTEM

The proposed system aims to create an intelligent and interactive interface that allows users to interact with computers using hand gestures and sign language recognition, offering a non-verbal, intuitive, and accessible method of communication. This system is especially beneficial for individuals with speech or hearing impairments, as it enables interaction without the need for traditional input devices such as keyboards, mice, or voice commands. At the core of the proposed system lies a real-time video capture module that utilizes a standard webcam to detect hand movements and gestures. This video stream serves as input to a computer vision pipeline that performs hand detection, segmentation, and feature extraction. To achieve accurate hand and gesture tracking, the system employs advanced image preprocessing techniques including background subtraction, skin color segmentation, and morphological operations to isolate the hand region from complex backgrounds. Following this, a deep learning-based recognition module, specifically using Convolutional Neural Networks (CNNs), is trained on a dataset of static and dynamic hand gestures as well as sign language alphabets and words. The CNN model is capable of learning spatial hierarchies of features from the input images, allowing it to distinguish between subtle differences in hand shapes and movements.

In addition to CNNs, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) units, are integrated into the system to handle dynamic gestures and continuous sign language recognition, capturing the temporal aspects of hand motion over a sequence of frames. These models are trained on annotated datasets of American Sign Language (ASL) or other regional sign languages to enhance the system's linguistic coverage and adaptability. The recognized gestures or signs are then mapped to predefined commands or translated into text or speech output, allowing the system to serve both as a control interface and a communication aid. A key component of the proposed system is its real-time responsiveness, achieved through optimization techniques and lightweight model architectures that ensure low latency even on standard computing devices without requiring dedicated GPUs. Furthermore, a user-friendly graphical user interface (GUI) is designed to provide visual feedback, display recognized gestures, and allow customization of gesture-command mappings. This enhances user interaction and learning, especially for new users unfamiliar with gesture-based systems.

To ensure robustness and scalability, the system is designed to operate under various environmental conditions, including different lighting, skin tones, and backgrounds. Data augmentation techniques such as rotation, scaling, and brightness adjustment are applied during training to improve the generalization of the recognition models. In addition, the system incorporates a calibration step where users can define or retrain specific gestures to tailor the interface to their unique hand shapes or movement patterns. This adaptability makes the system suitable for a wide range of users with different physical capabilities. The proposed system is evaluated through both quantitative metrics (e.g., recognition accuracy, processing time) and qualitative user studies involving participants from diverse backgrounds, including members of the Deaf and Hard-of-Hearing (DHH) community. User feedback is collected to assess the system's usability, intuitiveness, and effectiveness in real-world scenarios. These insights inform iterative improvements in both the gesture recognition models and the interface design.

Ultimately, this system aims to contribute meaningfully to the field of accessible computing by offering a practical, scalable, and inclusive solution for gesture-based human-computer interaction. It serves as both a communication bridge for sign language users and a general-purpose interface for hands-free control, with potential applications in education, healthcare, smart home environments, and virtual reality. Future extensions of the system may include multilingual sign language support, integration with wearable devices, and deployment on mobile platforms, further enhancing its portability and impact.

4. RESULTS

The proposed system was developed to enable intuitive computer interaction using both hand gestures and sign language recognition. It was rigorously evaluated based on recognition accuracy, system performance (latency and frame rate), user feedback, and comparison with existing technologies. The following subsections detail the experimental setup and corresponding results.

4.1 Gesture Recognition Accuracy

The system was trained and tested using a custom dataset comprising 1,500 labeled images. These included 15 distinct hand gestures and signs, including standard American Sign Language (ASL) representations. An 80:20 train-test split was used, and five-fold cross-validation (k=5) was employed to ensure robustness and generalizability of the model.

The gesture recognition engine was built on a Convolutional Neural Network (CNN) architecture, which was selected for its ability to extract spatial features from hand images effectively. The model achieved an **average classification accuracy of 94.2%** on the test set. High precision and recall were noted across most gesture classes. However, accuracy varied slightly among classes, particularly in gestures with visually similar features.

The individual class accuracies are summarized in Table 1. For instance, gestures like "Open Palm" and "Thumbs Up" consistently achieved accuracies above 96%, while signs such as ASL “M” and “N” showed slightly reduced performance due to visual similarity and overlapping finger positions.

4.2 System Latency and Responsiveness

Real-time responsiveness is critical for effective human-computer interaction. The system was benchmarked to assess latency and frame processing capability under typical usage conditions. The **average latency** — measured as the time between gesture input and corresponding system response — was approximately **220 milliseconds**, which is considered acceptable for real-time interaction.

Using OpenCV and GPU acceleration, the system consistently achieved a **frame processing rate of 12 to 15 frames per second (FPS)**. This performance ensures that users can interact with the interface fluidly without noticeable delay, making it suitable for practical deployment in accessibility tools or interactive environments.

4.3 User Study and Feedback

To evaluate the system from an end-user perspective, a usability study was conducted involving **20 participants**. The cohort included two groups: **10 individuals proficient in American Sign Language (ASL)** and **10 general users** without prior experience in sign language.

Participants were asked to perform a series of gestures and sign-based commands using the system. After completing the tasks, they provided feedback through structured questionnaires using a 5-point Likert scale. The following were the key findings:

- **Recognition Accuracy Satisfaction**: 4.5/5 – Users reported a high level of satisfaction with the gesture recognition capability.
- **Ease of Use**: 4.2/5 – The interface was generally perceived as intuitive and easy to use.

- **Perceived Error Rate**: Approximately 6.8% – Users encountered occasional recognition errors, primarily with similar-looking signs.
- **Preference over Traditional Inputs**: 65% of users expressed a preference for using gesture-based interaction over traditional devices like a mouse or keyboard for specific tasks, especially accessibility functions and presentations.

Qualitative feedback indicated that users appreciated the system's responsiveness and the hands-free nature of interaction, particularly those with mobility impairments.

4.4 Confusion Matrix Analysis

To further analyze classification performance, a confusion matrix was generated. While most gesture classes showed high precision and recall, **confusion was observed between visually similar gestures**, especially between ASL signs such as **“M” and “N”**, and between gestures with partially occluded finger positions.

This suggests that although the CNN model performs well overall, **gesture disambiguation remains a challenge** when dealing with minimal inter-class variation. Future work will focus on enhancing the spatial-temporal modeling of gestures using techniques such as 3D CNNs or recurrent neural networks (RNNs), as well as incorporating depth information and motion vectors to distinguish subtle hand movements.

4.5 Comparison with Existing Systems

The proposed system was compared against leading gesture recognition frameworks, including **Google's MediaPipe** and **Leap Motion Controller**. The comparison focused on recognition accuracy, hardware dependency, and ease of integration.

While **Leap Motion** showed slightly higher accuracy, it requires proprietary hardware, limiting accessibility and scalability. **MediaPipe** is accessible and efficient but has limited out-of-the-box support for dynamic or complex signs. In contrast, the proposed system **achieves a balance between performance and accessibility**, requiring only a standard webcam while supporting both static and dynamic gestures.

5. CONCLUSION

This paper presented a novel approach to computer interaction using hand gestures and sign language recognition, emphasizing accessibility and real-time interaction. The proposed system, built on a Convolutional Neural Network (CNN) architecture, was evaluated using a custom dataset consisting of 1,500 labeled images of 15 distinct gestures and American Sign Language (ASL) signs. The system demonstrated a strong recognition accuracy of 94.2%, highlighting its potential for use in diverse applications, including human-computer interaction and accessibility tools for the hearing impaired.

The performance of the system in terms of latency and responsiveness was also commendable, with an average latency of just 220 milliseconds and frame processing rates between 12 and 15 frames per second, ensuring that users could interact with the system in real time. User feedback from a study involving both sign language proficient and non-proficient participants revealed high levels of satisfaction with the system's usability and gesture recognition accuracy, with 65% of participants preferring it over traditional input methods.

However, some challenges remain, particularly regarding the misclassification of similar-looking gestures, such as the ASL "M" and "N" signs. This issue points to the need for enhanced disambiguation techniques in future iterations of the system. Despite this, the system demonstrated significant advantages over existing solutions like **MediaPipe** and **Leap Motion**, especially in terms of accessibility, ease of integration, and hardware requirements, making it a promising solution for widespread adoption.

In conclusion, the system presented here offers an innovative and practical interface for computer interaction through gestures and sign language recognition. Future work will focus on improving accuracy, particularly for visually similar signs, and expanding the system's capabilities for more complex interactions, moving towards a more inclusive and intuitive way for individuals with diverse needs to interact with digital systems.

REFERENCES

1. Rajakannu, A., Ramachandran, K. P., & Vijayalakshmi, K. (2024). Condition Monitoring of Drill Bit for Manufacturing Sector Using Wavelet Analysis and Artificial Neural Network (ANN).
2. Sakthibalan, P., Saravanan, M., Ansal, V., Rajakannu, A., Vijayalakshmi, K., & Vani, K. D. (2023). A Federated Learning Approach for ResourceConstrained IoT Security Monitoring. In *Handbook on Federated Learning* (pp. 131-154). CRC Press.
3. Amuthakkannan, R., & Al Yaqoubi, M. H. A. (2023). Development of IoT based water pollution identification to avoid destruction of aquatic life and to improve the quality of water. *International journal of engineering trends and technology*, *71*(10), 355-370.
4. Amuthakkannan, R., Vijayalakshmi, K., Kamarunisha, M., Kumar, S. G., Ajithkumar, P., & Vikram, P. (2023). Optimization of multi parameters of WEDM using ANN based on principal component analysis for AA6063/B4C metal matrix composites. *Materials Today: Proceedings*.
5. Amuthakkannan, R., Muthuraj, M., Ademi, E., Rajesh, V., & Ahammad, S. H. (2023). Analysis of fatigue strength on friction stir lap weld AA2198/Ti6Al4V joints. *Materials Today: Proceedings*.
6. Sidharth, S. (2017). Cybersecurity Approaches for IoT Devices in Smart City Infrastructures.
7. Sidharth, S. (2016). The Role of Artificial Intelligence in Enhancing Automated Threat Hunting 1Mr. Sidharth Sharma.
8. Sivakumar, K., Perumal, T., Yaakob, R., & Marlisah, E. (2024, March). Unobstructive human activity recognition: Probabilistic feature extraction with optimized convolutional neural network for classification. In *AIP Conference Proceedings* (Vol. 2816, No. 1). AIP Publishing.
9. Kalimuthu, S., Perumal, T., Yaakob, R., Marlisah, E., & Raghavan, S. (2024, March). Multiple human activity recognition using iot sensors and machine learning in device-free environment: Feature extraction, classification, and challenges: A comprehensive review. In *AIP Conference Proceedings* (Vol. 2816, No. 1). AIP Publishing.
10. Bs, V., Madamanchi, S. C., & Kalimuthu, S. (2024, February). Early Detection of Down Syndrome Through Ultrasound Imaging Using Deep Learning Strategies—A Review. In *2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE)* (pp. 1-6). IEEE.
11. Kalimuthu, S., Ponkoodanlingam, K., Jeremiah, P., Eaganathan, U., & Juslen, A. S. A. (2016). A comprehensive analysis on current botnet weaknesses and improving the security performance on botnet monitoring and detection in peer-to-peer botnet. *Iarjset*, *3*(5), 120-127.
12. Kalimuthu, S., Perumal, T., Marlisah, E., Yaakob, R., BS, V., & Ismail, N. H. (2024). HUMAN ACTIVITY RECOGNITION BASED ON DEVICE-FREE WI-FI SENSING: A COMPREHENSIVE REVIEW. *Malaysian Journal of Computer Science*, *37*(3), 252-269.
13. Sidharth, S. (2018). Post-Quantum Cryptography: Readying Security for the Quantum Computing Revolution.
14. Sidharth, S. (2019). DATA LOSS PREVENTION (DLP) STRATEGIES IN CLOUD-HOSTED APPLICATIONS.
15. Srinivasan, R. (2025). Friction Stir Additive Manufacturing of AA7075/Al2O3 and Al/MgB2 Composites for Improved Wear and Radiation Resistance in Aerospace Applications. *J. Environ. Nanotechnol*, *14*(1), 295-305.
16. Vijayalakshmi, K., Amuthakkannan, R., Ramachandran, K., & Rajkavin, S. A. (2024). Federated Learning-Based Futuristic Fault Diagnosis and Standardization in Rotating Machinery. *SSRG International Journal of Electronics and Communication Engineering*, *11*(9), 223-236.
17. Rajakannu, A. (2024). Implementation of Quality Function Deployment to Improve Online Learning and Teaching in Higher Education Institutes of Engineering in Oman. *International Journal of Learning, Teaching and Educational Research*, *23*(12), 463-486.

18. Rajakannu, A., Ramachandran, K. P., & Vijayalakshmi, K. (2024). Application of Artificial Intelligence in Condition Monitoring for Oil and Gas Industries.
19. Al Haddabi, T., Rajakannu, A., & Al Hasni, H. (2024). Design and Development of a Low-Cost Parabolic Type Solar Dryer and Its Performance Evaluation in Drying of King Fish–Case Study in Oman.
20. Sidharth, S. (2015). AI-Driven Detection and Mitigation of Misinformation Spread in Generated Content.
21. Sidharth, S. (2015). Privacy-Preserving Generative AI for Secure Healthcare Synthetic Data Generation.
22. Kalimuthu, S., Perumal, T., Yaakob, R., Marlisah, E., & Babangida, L. (2021, March). Human Activity Recognition based on smart home environment and their applications, challenges. In *2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)* (pp. 815-819). IEEE.
23. Vidhyasagar, B. S., Lakshmanan, A. S., Abishek, M. K., & Kalimuthu, S. (2023, October). Video captioning based on sign language using yolov8 model. In *IFIP International Internet of Things Conference* (pp. 306-315). Cham: Springer Nature Switzerland.
24. Ramanujam, E., Kalimuthu, S., Harshavardhan, B. V., & Perumal, T. (2023, October). Improvement in Multi-resident Activity Recognition System in a Smart Home Using Activity Clustering. In *IFIP International Internet of Things Conference* (pp. 316-334). Cham: Springer Nature Switzerland.
25. Vidhyasagar, B. S., Arvindhan, M., Arulprakash, A., Kannan, B. B., & Kalimuthu, S. (2023, November). The crucial function that clouds access security brokers play in ensuring the safety of cloud computing. In *2023 International Conference on Communication, Security and Artificial Intelligence (ICCSAI)* (pp. 98-102). IEEE.
26. Vidhyasagar, B. S., Harshagnan, K., Diviya, M., & Kalimuthu, S. (2023, October). Prediction of Tomato Leaf Disease Plying Transfer Learning Models. In *IFIP International Internet of Things Conference* (pp. 293-305). Cham: Springer Nature Switzerland.
27. Sidharth, S. (2017). Access Control Frameworks for Secure Hybrid Cloud Deployments.
28. Sidharth, S. (2016). Establishing Ethical and Accountability Frameworks for Responsible AI Systems.
29. Turlapati, V. R., Thirunavukkarasu, T., Aiswarya, G., Thoti, K. K., Swaroop, K. R., & Mythily, R. (2024, November). The Impact of Influencer Marketing on Consumer Purchasing Decisions in the Digital Age Based on Prophet ARIMA-LSTM Model. In *2024 International Conference on Integrated Intelligence and Communication Systems (ICIICS)* (pp. 1-6). IEEE.
30. Turlapati, V. R., Vichitra, P., Raval, N., Khaja Mohinuddeen, J., & Mishra, B. R. (2024). Ethical Implications of Artificial Intelligence in Business Decision-making: A Framework for Responsible AI Adoption. *Journal of Informatics Education and Research*, *4*(1).
31. Sreekanthaswamy, N., Anitha, S., Singh, A., Jayadeva, S. M., Gupta, S., Manjunath, T. C., & Selvakumar, P. (2025). Digital Tools and Methods. *Enhancing School Counseling With Technology and Case Studies*, *25*.
32. Kalluri, S. V. S., & Narra, S. (2024). Predictive Analytics in ADAS Development: Leveraging CRM Data for Customer-Centric Innovations in Car Manufacturing. *vol*, *9*, 6.
33. Devi, K., & Indoria, D. (2021). Role of Micro Enterprises in the Socio-Economic Development of Women--A Case Study of Koraput District, Odisha. *Design Engineering*, 1135-1151.
34. Indoria, D. (2021). AN APPLICATION OF FOREIGN DIRECT INVESTMENT. *BIMS International Research Journal of Management and Commerce*, *6*(1), 01-04.
35. Raja, D. R. K., Abas, Z. A., Kumar, G. H., Murthy, C. R., & Eswari, V. (2024). Hybrid optimization algorithm for resource-efficient and data-driven performance in agricultural IoT. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, *23*(1), 201-210.
36. Selvaprasanth, P., Karthick, R., Meenalochini, P., & Prabaharan, A. M. (2025). FPGA implementation of hybrid Namib beetle and battle royale optimization algorithm fostered linear phase finite impulse response filter design. *Analog Integrated Circuits and Signal Processing*, *123*(2), 33.

37. Deepa, R., Karthick, R., & Senthilkumar, R. (2025). Performance analysis of multiple-input multiple-output orthogonal frequency division multiplexing system using arithmetic optimization algorithm. *Computer Standards & Interfaces*, *92*, 103934.

38. Kumar, T. V., Karthick, R., Nandhini, C., Annalakshmi, M., & Kanna, R. R. (2025). 20 GaN Power HEMT-Based Amplifiers. *Circuit Design for Modern Applications*, 320.
39. Geeitha, S., & Thangamani, M. (2018). Incorporating EBO-HSIC with SVM for gene selection associated with cervical cancer classification. *Journal of medical systems*, *42*(11), 225.
40. Thangamani, M., & Thangaraj, P. (2010). Integrated Clustering and Feature Selection Scheme for Text Documents. *Journal of Computer Science*, *6*(5), 536.
41. Gangadhar, C., Chanthirasekaran, K., Chandra, K. R., Sharma, A., Thangamani, M., & Kumar, P. S. (2022). An energy efficient NOMA-based spectrum sharing techniques for cell-free massive MIMO. *International Journal of Engineering Systems Modelling and Simulation*, *13*(4), 284-288.
42. Narmatha, C., Thangamani, M., & Ibrahim, S. J. A. (2020). Research scenario of medical data mining using fuzzy and graph theory. *International Journal of Advanced Trends in Computer Science and Engineering*, *9*(1), 349-355.
43. Thangamani, M., & Thangaraj, P. (2013). Fuzzy ontology for distributed document clustering based on genetic algorithm. *Applied Mathematics & Information Sciences*, *7*(4), 1563-1574.
44. Anandasubramanian, C. P., & Selvaraj, J. (2024). NAVIGATING BANKING LIQUIDITY-FACTORS, CHALLENGES, AND STRATEGIES IN CORPORATE LOAN PORTFOLIOS. *Tec Empresarial*, *6*(1).
45. Madem, S., Katuri, P. K., Kalra, A., & Singh, P. (2023, May). System Design for Financial and Economic Monitoring Using Big Data Clustering. In *2023 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)* (pp. 1-7). IEEE.
46. Srikanth, V., & Dhanapal, D. R. (2012). E-commerce online security and trust marks. *International Journal of Computer Engineering and Technology*, *3*(2), 238-255.
47. Srikanth, V., Walia, R., Augustine, P. J., Simla, J., & Jegajothi, B. (2022, March). Chaotic Whale Optimization based Node Localization Protocol for Wireless Sensor Networks Enabled Indoor Communication. In *2022 International Conference on Electronics and Renewable Systems (ICEARS)* (pp. 702-707). IEEE.
48. Srikanth, V., Natarajan, V., Jegajothi, B., Arumugam, S. D., & Nageswari, D. (2022, March). Fruit fly optimization with deep learning based reactive power optimization model for distributed systems. In *2022 International Conference on Electronics and Renewable Systems (ICEARS)* (pp. 319-324). IEEE.
49. Singh, S., Srikanth, V., Kumar, S., Saravanan, L., Degadwala, S., & Gupta, S. (2022, February). IOT Based Deep Learning framework to Diagnose Breast Cancer over Pathological Clinical Data. In *2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM)* (Vol. 2, pp. 731-735). IEEE.
50. Srikanth, V., & Dhanapal, R. (2011). A business review of e-retailing in India. *International journal of business research and management*, *1*(3), 105-121.
51. Shinkar, A. R., Joshi, D., Praveen, R. V. S., Rajesh, Y., & Singh, D. (2024, December). Intelligent solar energy harvesting and management in IoT nodes using deep self-organizing maps. In *2024 International Conference on Emerging Research in Computational Science (ICERCS)* (pp. 1-6). IEEE.
52. Praveen, R. V. S., Hemavathi, U., Sathya, R., Siddiq, A. A., Sanjay, M. G., & Gowdish, S. (2024, October). AI Powered Plant Identification and Plant Disease Classification System. In *2024 4th International Conference on Sustainable Expert Systems (ICSES)* (pp. 1610-1616). IEEE.
53. Dhivya, R., Sagili, S. R., Praveen, R. V. S., VamsiLala, P. N. V., Sangeetha, A., & Suchithra, B. (2024, December). Predictive Modelling of Osteoporosis using Machine Learning Algorithms. In *2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS)* (pp. 997-1002). IEEE.
54. Kemmannu, P. K., Praveen, R. V. S., Saravanan, B., Amshavalli, M., & Banupriya, V. (2024, December). Enhancing Sustainable Agriculture Through Smart Architecture: An Adaptive Neuro-Fuzzy Inference System with XGBoost Model. In *2024 International Conference on Sustainable Communication Networks and Application (ICSCNA)* (pp. 724-730). IEEE.
55. Praveen, R. V. S. (2024). *Data Engineering for Modern Applications*. Addition Publishing House.
56. Surendiran, R., Aarthi, R., Thangamani, M., Sugavanam, S., & Sarumathy, R. (2022). A Systematic Review Using Machine Learning Algorithms for Predicting Preterm Birth. *International Journal of Engineering Trends and Technology*, *70*(5), 46-59.

57. Thangamani, M., & Thangaraj, P. (2010). Ontology based fuzzy document clustering scheme. *Modern Applied Science*, *4*(7), 148.
58. Ibrahim, S. J. A., & Thangamani, M. (2018, November). Momentous Innovations in the prospective method of Drug development. In *Proceedings of the 2018 International Conference on Digital Medicine and Image Processing* (pp. 37-41).
59. Ramesh, T. R., Lilhore, U. K., Poongodi, M., Simaiya, S., Kaur, A., & Hamdi, M. (2022). Predictive analysis of heart diseases with machine learning approaches. *Malaysian Journal of Computer Science*, 132-148.
60. Ramesh, T. R., Vijayaragavan, M., Poongodi, M., Hamdi, M., Wang, H., & Bourouis, S. (2022). Peer-to-peer trust management in intelligent transportation system: An Aumann's agreement theorem based approach. *ICT Express*, *8*(3), 340-346.
61. Ramesh, T. R., & Kavitha, C. (2013). Web user interest prediction framework based on user behavior for dynamic websites. *Life Sci. J*, *10*(2), 1736-1739.
62. Ali, A., Naeem, S., Anam, S., & Ahmed, M. M. (2022). Machine learning for intrusion detection in cyber security: Applications, challenges, and recommendations. *UMT Artif. Intell. Rev*, *2*(2), 41-64.
63. Ramesh, T. R., Raghavendra, R., Vantamuri, S. B., Pallavi, R., & Easwaran, B. (2023). IMPROVING THE QUALITY OF VANET COMMUNICATION USING FEDERATED PEER-TO-PEER LEARNING. *ICTACT Journal on Communication Technology*, *14*(1).
64. Kalaiselvi, B., & Thangamani, M. (2020). An efficient Pearson correlation based improved random forest classification for protein structure prediction techniques. *Measurement*, *162*, 107885.
65. Prabhu Kavin, B., Karki, S., Hemalatha, S., Singh, D., Vijayalakshmi, R., Thangamani, M., ... & Adigo, A. G. (2022). Machine learning-based secure data acquisition for fake accounts detection in future mobile communication networks. *Wireless Communications and Mobile Computing*, *2022*(1), 6356152.
66. Lopez, S., Sarada, V., Praveen, R. V. S., Pandey, A., Khuntia, M., & Haralayya, D. B. (2024). Artificial intelligence challenges and role for sustainable education in india: Problems and prospects. *Sandeep Lopez, Vani Sarada, RVS Praveen, Anita Pandey, Monalisa Khuntia, Bhadrappa Haralayya (2024) Artificial Intelligence Challenges and Role for Sustainable Education in India: Problems and Prospects. Library Progress International*, *44*(3), 18261-18271.
67. Yamuna, V., Praveen, R. V. S., Sathya, R., Dhivva, M., Lidiya, R., & Sowmiya, P. (2024, October). Integrating AI for Improved Brain Tumor Detection and Classification. In *2024 4th International Conference on Sustainable Expert Systems (ICSES)* (pp. 1603-1609). IEEE.
68. Kumar, N., Kurkute, S. L., Kalpana, V., Karuppannan, A., Praveen, R. V. S., & Mishra, S. (2024, August). Modelling and Evaluation of Li-ion Battery Performance Based on the Electric Vehicle Tiled Tests using Kalman Filter-GBDT Approach. In *2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS)* (pp. 1-6). IEEE.
69. Sharma, S., Vij, S., Praveen, R. V. S., Srinivasan, S., Yadav, D. K., & VS, R. K. (2024, October). Stress Prediction in Higher Education Students Using Psychometric Assessments and AOA-CNN-XGBoost Models. In *2024 4th International Conference on Sustainable Expert Systems (ICSES)* (pp. 1631-1636). IEEE.
70. Anuprathibha, T., Praveen, R. V. S., Sukumar, P., Suganthi, G., & Ravichandran, T. (2024, October). Enhancing Fake Review Detection: A Hierarchical Graph Attention Network Approach Using Text and Ratings. In *2024 Global Conference on Communications and Information Technologies (GCCIT)* (pp. 1-5). IEEE.
71. Jayapandiyan, J. R., Kavitha, C., & Sakthivel, K. (2020). Enhanced least significant bit replacement algorithm in spatial domain of steganography using character sequence optimization. *Ieee Access*, *8*, 136537-136545.
72. Sakthivel, K., Jayanthiladevi, A., & Kavitha, C. (2016). Automatic detection of lung cancer nodules by employing intelligent fuzzy c-means and support vector machine. *BIOMEDICAL RESEARCH-INDIA*, *27*, S123-S127.
73. Sakthivel, K., Nallusamy, R., & Kavitha, C. (2014). Color image segmentation using SVM pixel classification image. *World Academy of Science, Engineering and Technology International Journal of Computer, Electrical, Automation, Control and Information Engineering*, *8*(10), 1924-1930.
74. Jayapandiyan, J. R., Kavitha, C., & Sakthivel, K. (2020). Optimal secret text compression technique for steganographic encoding by dynamic ranking algorithm. In *Journal of Physics: Conference Series* (Vol. 1427, No. 1, p. 012005). IOP Publishing.

75. Sakthivel, K., Abinaya, R., Nivetha, I., & Kumar, R. A. (2014). Region based image retrieval using k-means and hierarchical clustering algorithms. *International Journal of Innovative Research in Science, Engineering and Technology*, *3*(1), 1255-1260.
76. Prasad, V., Dangi, A. K., Tripathi, R., & Kumar, N. (2023). Educational Perspective of Intellectual Property Rights. *Russian Law Journal*, *11*(2S), 257-268.
77. Shreevamshi, D. V. K., Jadhavar, S. S., Vemuri, V. P., & Kumar, A. (2022). Role Of Green HRM in Advocating Pro-Environmental Behavior Among Employees. *Journal of Positive School Psychology*, *6*(2), 3117-3129.
78. Somasundaram, R., Chandra, S., Tamilarasu, J., Kinagi, A. M., & Naveen, S. (2025). Human Resource Development (HRD) Strategies for Emerging Entrepreneurship: Leveraging UX Design for Sustainable Digital Growth. In *Navigating Usability and User Experience in a Multi-Platform World* (pp. 221-248). IGI Global.
79. Khachariya, H. D., Naveen, S., Al-Nussairi, A. K. J., Abood, B. S. Z., Alanssari, A. I., & Shaker, Z. Y. (2024, November). Deep Learning for Workforce Planning and Analytics. In *2024 Second International Conference Computational and Characterization Techniques in Engineering & Sciences (IC3TES)* (pp. 1-5). IEEE.
80. Perumal, R. A. (2025). Innovative Applications of AI and Machine Learning in Fraud Detection for Insurance Claims. *JOURNAL OF ADVANCE AND FUTURE RESEARCH*, *3*(2), 18-23.
81. Thamma, S. R. T. S. R. (2024). Optimization of Generative AI Costs in Multi-Agent and Multi-Cloud Systems.
82. Thamma, S. R. T. S. R. (2024). Revolutionizing Healthcare: Spatial Computing Meets Generative AI.