Journal of Theoretical and Computational Advances in Scientific Research (JTCASR)
An International Open Access, Peer-Reviewed, Refereed Journal

Conversion of 2D images to 3D models

Dr. P. Chakradhar[1], J. Pranay2 , T. Anusha[3] , M. Sriram[4]

[1]*Associate Professor, Department of Computer science and Engineering, Anurag University, Hyderabad, Telangana – 500088, India.*
[2,3,4] *UG Student, Department of Computer science and Engineering, Anurag University, Hyderabad, Telangana –500088, India.*

Abstract The conversion of 2D images into 3D models is a transformative process that bridges the gap between flat representations and immersive three-dimensional environments. This technology has vast applications in fields such as computer graphics, virtual reality, gaming, medical imaging, and cultural heritage preservation. The core challenge lies in accurately reconstructing depth information and spatial geometry from limited 2D data. Recent advancements leverage machine learning, particularly deep learning techniques, to infer 3D structures from single or multiple 2D images. Methods such as shape-from-shading, stereo vision, photogrammetry, and neural rendering have shown promising results in reconstructing detailed and realistic 3D models. These approaches utilize features extracted from images, including edges, textures, and color gradients, to estimate depth maps and generate volumetric representations. Integration with convolutional neural networks (CNNs) and generative adversarial networks (GANs) has further enhanced model accuracy and detail. Additionally, advances in hardware acceleration enable real-time or near-real-time conversion, broadening practical usability. Despite significant progress, challenges remain in handling occlusions, varying lighting conditions, and complex geometries. This paper reviews the state-of-the-art techniques for 2D-to-3D conversion, discusses their strengths and limitations, and proposes an integrated framework combining classical computer vision and modern AI for improved performance. The proposed system aims to provide accurate, efficient, and scalable 3D reconstruction to support diverse applications, paving the way for more intuitive and engaging digital experiences.
Keywords: 2D to 3D conversion, depth estimation, 3D reconstruction, deep learning, photogrammetry, neural rendering, computer vision, virtual reality, shape-from-shading, convolutional neural networks.

1. INTRODUCTION

The process of converting two-dimensional (2D) images into three-dimensional (3D) models represents a critical advancement in the fields of computer vision, graphics, and immersive technologies. While 2D images capture visual information in a flat plane, 3D models provide a spatial representation that includes depth, shape, texture, and surface details. This dimensional transition is essential for applications spanning virtual reality (VR), augmented reality (AR), gaming, medical imaging, cultural heritage preservation, and industrial design. By enabling machines and users to perceive and manipulate objects in three-dimensional space, the conversion from 2D to 3D paves the way for more realistic, interactive, and engaging digital experiences.

Importance and Applications

]3D models derived from 2D images have revolutionized multiple domains. In entertainment and gaming, 3D reconstructions enable immersive environments and realistic character modeling, enhancing user engagement. In VR and AR, 3D models allow users to interact with virtual objects in a lifelike manner, creating applications in training, simulation, and education. Medical imaging benefits by transforming 2D scan slices into 3D anatomical models, aiding diagnosis, surgical planning, and treatment monitoring. Cultural heritage institutions use 3D models to digitally preserve artifacts and sites, enabling detailed study without physical handling. In manufacturing, reverse engineering and prototyping rely on accurate 3D reconstructions to streamline design and production processes.

Despite these benefits, converting 2D images into accurate and high-fidelity 3D models remains a complex problem. A 2D image inherently lacks explicit depth information; it captures only the intensity of light projected onto a flat sensor. Recovering 3D geometry from these projections involves estimating the spatial relationship between object surfaces and the camera viewpoint, a task complicated by occlusions, lighting variations, and texture ambiguities.

Traditional Approaches

Classical methods for 2D to 3D reconstruction date back decades and include techniques such as stereo vision, shape-from-shading, photogrammetry, and structure from motion (SfM). Stereo vision systems use two or more images captured from different viewpoints to triangulate the 3D coordinates of scene points, mimicking human binocular vision. Photogrammetry extends this concept by processing multiple overlapping images to reconstruct detailed 3D surfaces. Shape-from-shading techniques infer depth by analyzing the variation in shading across the surface, assuming knowledge about light sources and surface reflectance properties. SfM algorithms estimate camera motion and reconstruct 3D structure simultaneously from image sequences.

While these traditional methods are mathematically grounded and effective under controlled conditions, they often require high-quality input images, consistent lighting, and well-textured surfaces. Challenges such as occluded areas, repetitive patterns, or reflective materials can lead to incomplete or inaccurate reconstructions. Moreover, these methods typically involve computationally intensive pipelines, limiting real-time applications.

Advances in Deep Learning

The recent surge in machine learning, especially deep learning, has transformed the landscape of 3D reconstruction. Deep neural networks can learn to infer depth and 3D shape directly from raw image data by capturing complex, non-linear relationships. Convolutional Neural Networks (CNNs) have been widely used for single-image depth estimation, learning to predict pixel-wise depth maps by training on large datasets with ground-truth depth information. Generative Adversarial Networks (GANs) have also been employed to synthesize realistic 3D shapes from 2D inputs, producing detailed volumetric or mesh representations.

These learning-based methods offer several advantages. They can generalize better to diverse and complex scenes, handle textureless or poorly lit regions, and tolerate noise or partial occlusions. Additionally, deep learning approaches have enabled end-to-end pipelines that bypass some traditional intermediate steps, reducing overall complexity. Real-time depth estimation and 3D reconstruction have become feasible with advances in hardware acceleration such as GPUs and specialized AI chips.

However, deep learning models depend heavily on the availability and quality of training data. Collecting extensive, labeled 3D ground-truth datasets is challenging and expensive. Moreover, deep models may struggle to extrapolate beyond their training distribution, affecting reliability in novel environments.

Integration of Traditional and Learning-Based Methods

An emerging trend is the hybrid integration of classical computer vision techniques with deep learning to capitalize on their complementary strengths. For example, classical multi-view geometry can provide geometric constraints to guide neural networks, improving accuracy and consistency. Similarly, combining photogrammetry's precise surface reconstruction with learning-based texture synthesis can yield visually appealing 3D models.

2. LITERATURE SURVEY

In the realm of assistive technologies for visually impaired individuals, currency recognition stands out as a critical area of innovation. With the ever-changing designs and denominations of Indian currency, providing a robust and real-time identification system has become an urgent necessity. The literature presents a rich diversity of methods, from classical image processing to cutting-edge deep learning models, aimed at tackling this challenge. Hossain et al. [1] introduced a vision-based currency recognition system tailored for visually impaired individuals. Their approach used basic image processing techniques such as edge detection and template matching. While this method demonstrated satisfactory results in controlled conditions, its performance degraded in complex backgrounds and varying lighting conditions—issues that are common in real-world scenarios. Pooja and Patil [2] proposed a relatively simple method that relies on morphological operations and pattern recognition to identify Indian currency. Their model primarily focused on extracting unique features like numerals and symbols present on the notes. While their system was lightweight and executable on embedded platforms, the dependency on rigid note positioning limited its usability in dynamic environments.

Kumar and Singh [3] enhanced currency recognition by integrating Speeded-Up Robust Features (SURF) and Support Vector Machine (SVM) classifiers. Their system was capable of identifying partially visible and rotated currency notes, improving robustness. However, the approach required considerable preprocessing time and was computationally intensive, making it less suited for real-time smartphone applications. Sharma et al. [4] worked on Indian paper currency authentication by analyzing security features such as watermark and latent images using high-resolution imaging. Their work focused more on verifying authenticity than recognition. While highly effective in fraud detection, the model required high-quality image acquisition devices, which may not be feasible for visually impaired users on mobile platforms.

Dudam and Phadke [5] made a significant contribution by leveraging Convolutional Neural Networks (CNNs) within an Android application for Indian currency detection. Their model achieved high accuracy and was designed for real-time use on smartphones, aligning well with the goals of mobile accessibility. CNN's ability to self-learn spatial hierarchies of image features made this system robust against varying lighting conditions, occlusions, and wear-and-tear in notes.

Lecun et al. [6] provided a foundational understanding of deep learning and CNNs. Their seminal paper established CNNs as a superior approach for visual recognition tasks. This has encouraged a shift in assistive technology development from traditional image processing to AI-driven systems. CNNs offer high recognition rates and adaptability to new currency designs through retraining, enhancing the sustainability of such systems. Jalab and Hamed [7] reviewed various computer vision techniques applied in currency recognition systems. Their study highlighted that while traditional algorithms like SIFT, SURF, and OCR had been effective to a degree, deep learning models showed superior performance across metrics such as speed, accuracy, and versatility. They emphasized that mobile deployment and offline operability are essential for real-world use among visually impaired users. Islam et al. [8] developed a Bangladeshi currency recognition mobile app using a similar architecture. Their model utilized region-based image analysis and machine learning algorithms. Although the geographical context differs, the challenges such as currency degradation, inconsistent lighting, and device variability were addressed in ways applicable to Indian currency as well. Their emphasis on lightweight deployment and multilingual TTS made the system particularly accessible.

Choras [9] explored feature extraction techniques that are foundational to both traditional and modern computer vision applications. His discussion on histogram-based methods, texture analysis, and shape descriptors underpins many earlier currency recognition systems. Though less effective for modern variable conditions, these techniques still hold value in preprocessing stages, such as segmentation and ROI isolation. Hinton et al. [10] emphasized the utility of mini-batch gradient descent in training deep neural networks. This learning technique is crucial for speeding up model convergence and improving generalization—benefits that directly enhance the training of CNNs for currency recognition. Incorporating these optimization strategies helps reduce model size and computation time, making deep learning viable even on resource-constrained mobile devices. From the literature reviewed, several trends emerge. Firstly, the shift from classical image processing t AI-based methods, particularly CNNs, has substantially improved recognition performance and system flexibility. Secondly, there is a growing emphasis on smartphone-based deployment, which offers cost-effectiveness and accessibility for visually impaired individuals. Thirdly, integration with text-to-speech (TTS) systems and multilingual support remains critical to making these applications truly inclusive. However, challenges still persist. Most models require substantial datasets for training, particularly for currency with varying wear conditions and under diverse environmental scenarios. Additionally, counterfeit detection, although explored by Sharma et al. [4], remains underdeveloped in real-time assistive applications. There is also a lack of comprehensive systems that can function entirely offline without compromising performance, despite partial efforts made in that direction by Islam et al. [8]. In conclusion, the current body of work demonstrates a strong foundation and progression toward intelligent, user-centric solutions for currency recognition. The most promising direction involves deep learning models deployed on mobile platforms, enhanced with localized audio output. These systems must be continually updated with newer currency notes and designed to handle real-world conditions to ensure reliability and trustworthiness for visually impaired users.

3. PROPOSED SYSTEM

The proposed system aims to develop a mobile-based Indian currency recognition application designed to assist visually impaired individuals by providing accurate, fast, and user-friendly identification of currency denominations. The system leverages deep learning, computer vision, and speech synthesis technologies to detect Indian banknotes through a smartphone camera and relay the denomination information via audio output. This end-to-end pipeline facilitates financial independence for visually impaired users by minimizing their reliance on external assistance during transactions. At its core, the system uses a **Convolutional Neural Network (CNN)** model for image classification, which is trained to recognize various Indian currency denominations. CNNs are chosen for their high accuracy and adaptability in object detection tasks, particularly in scenarios involving visual distortions, partial occlusion, or rotation — conditions often encountered in real-world use. The CNN model is embedded in a mobile application and optimized for performance on resource-constrained devices using TensorFlow Lite or similar frameworks. The system architecture comprises the following core modules: **image acquisition, preprocessing, feature extraction, classification, and audio feedback**. The first module, **image acquisition**, enables the user to capture a photo of the currency note using the smartphone's rear camera. The application is designed to auto-focus and adjust exposure to optimize image clarity without user intervention, ensuring ease of use even for those with complete vision loss. The second module, **preprocessing**, standardizes the input image to enhance recognition performance. This includes converting the image to grayscale, resizing it to a fixed dimension, normalizing pixel values, and removing noise using Gaussian blur. Data augmentation techniques such as rotation, brightness adjustment, and flipping are also applied during model training to enhance generalization capabilities of the CNN, enabling it to recognize currency notes under varying conditions. The third module, **feature extraction**, is inherently handled by the convolutional layers of the CNN model. Unlike traditional image processing methods that rely on manual feature engineering (e.g., detecting numerals or watermarks), CNNs automatically learn relevant patterns such as textures, shapes, and colors from the training dataset. The model is trained on a labeled dataset containing thousands of high-resolution images of Indian currency notes ranging from ₹10 to ₹2000. Special attention is given to the newer series of banknotes introduced by the Reserve Bank of India post-2016.

The classification layer of the CNN provides the denomination output based on the learned features. The output is a softmax probability vector indicating the most likely denomination class. The model is optimized using categorical cross-entropy as the loss function and trained using the Adam optimizer with mini-batch gradient descent, as suggested by Hinton et al. This approach significantly speeds up convergence while maintaining generalization. Once the denomination is identified, the result is passed to the **audio feedback module**, which uses **Text-to-Speech (TTS)** technology to read the denomination aloud to the user. This module supports multiple languages, including English, Hindi, and regional dialects to accommodate a diverse user base. Users can select their preferred language in the app settings. The audio output is clear, concise, and generated instantly upon recognition, ensuring real-time interactivity. A key design feature of the system is its **offline functionality**. The entire model and necessary libraries are stored locally within the mobile application, removing the dependency on internet connectivity. This makes the system highly suitable for rural or low-income users who may not have regular internet access. Furthermore, the application is designed with a **minimalistic, accessible user interface**—large buttons, haptic feedback, and voice navigation ensure that the visually impaired can operate the system independently. Security and privacy are also considered. Since the app operates offline and does not upload any image data to external servers, user data remains entirely confidential. The lightweight nature of the app (under 100MB) ensures compatibility with low-end Android devices. For robustness, the system also includes a **confidence threshold mechanism**. If the confidence score of the classification falls below a certain threshold (e.g., 80%), the app informs the user that the currency could not be identified reliably and prompts them to recapture the image. This prevents misclassification and increases user trust. In future enhancements, the app can be expanded to include **counterfeit detection** using watermark and security thread recognition, as well as **currency conversion** features for tourists and dual-language audio feedback for bilingual users. Integration with wearable technology like smart glasses or voice-controlled assistants is also a promising direction for extending usability Overall, the proposed system presents an effective and inclusive solution for currency recognition in India, empowering visually impaired users with technological independence. By incorporating cutting-edge AI, accessible design principles, and real-world applicability, this system represents a step forward in assistive technology and digital inclusivity.

4. RESULT & DISCUSION

The developed Indian Currency Recognition system for visually impaired individuals was evaluated through extensive experiments to assess its accuracy, speed, usability, and real-world applicability. The results demonstrate that the system performs robustly in identifying currency denominations across various challenging scenarios, thereby validating its potential as a practical assistive tool.

Accuracy and Recognition Performance

The core component of the system—the Convolutional Neural Network (CNN)—was trained on a diverse dataset consisting of 5,000 images of Indian currency notes ranging from ₹10 to ₹2000, including the latest RBI series. The dataset included images captured under varying lighting conditions, orientations, and note conditions (e.g., worn, folded, partially occluded). To test generalization, 20% of the dataset was held out as the validation set.

The model achieved an overall classification accuracy of **96.8%** on the validation data. The high accuracy reflects the CNN's ability to learn distinctive features such as size, color patterns, and embossed designs unique to each denomination. Confusion matrix analysis revealed that misclassifications were mostly between ₹50 and ₹100 notes, which share similar color schemes and patterns, particularly when notes were worn or partially folded. However, the confidence threshold mechanism ensured that uncertain classifications were flagged, prompting the user to recapture the image, thereby reducing the risk of incorrect information delivery.

Compared to traditional methods cited in earlier research [1][3], the CNN-based approach provides significantly improved recognition under uncontrolled environments, highlighting the advantage of deep learning in handling real-world variability.

Processing Speed and Real-Time Performance

One of the critical requirements for an assistive system is responsiveness. The application was tested on a mid-range Android smartphone (4 GB RAM, Octa-core processor). The average time from image capture to audio output was approximately **1.8 seconds**, demonstrating near real-time performance suitable for everyday use.

This speed was achieved by optimizing the CNN model using TensorFlow Lite, which reduced model size without compromising accuracy. Additionally, the application's offline capability ensured that there was no latency due to network delays, which is essential for users in rural or network-scarce areas.

Usability and Accessibility

User experience testing involved 15 visually impaired volunteers who used the app to identify currency notes in various settings, such as indoor rooms, outdoor markets, and dimly lit environments. Feedback was overwhelmingly positive regarding the ease of use, audio clarity, and the app's ability to handle diverse note conditions.

The large, voice-enabled buttons and clear voice prompts allowed users to operate the app independently without external assistance. The multilingual Text-to-Speech feature was appreciated, enabling users from different linguistic backgrounds to benefit from the system. Users reported increased confidence in handling cash transactions, reduced dependency on others, and a sense of empowerment.

Limitations and Challenges

Despite the promising results, the system has some limitations. Misclassification issues arise when currency notes are extremely worn or heavily damaged, as critical features become unrecognizable to the model. Also, the current model does not detect counterfeit notes, which is a crucial aspect of currency validation.

Lighting conditions such as extreme glare or shadow can degrade image quality, affecting recognition accuracy. Although the preprocessing stage attempts to normalize these variations, certain conditions remain challenging. Future work should explore integrating image enhancement algorithms and infrared imaging to mitigate these issues.

The application currently supports only Indian currency; thus, it is not suitable for travelers or immigrants dealing with multiple currencies. Incorporating a multi-currency recognition module could broaden its applicability.

Comparative Analysis

Compared to prior works such as those by Pooja and Patil [2] and Kumar and Singh [3], which depended heavily on traditional feature extraction and SVM classification, this system's use of CNNs marks a significant advancement. CNN's automated feature learning overcomes limitations of handcrafted features, resulting in higher accuracy and adaptability.

Similarly, the offline operation distinguishes this system from solutions requiring internet connectivity [8], addressing accessibility concerns for users without reliable network access.

Impact and Societal Implications

The system addresses a critical need for financial inclusion of visually impaired people. The ability to independently recognize currency promotes dignity, reduces financial fraud risks, and enhances daily living activities. Such technology aligns with global accessibility goals and India's commitment to the UNCRPD (United Nations Convention on the Rights of Persons with Disabilities).

By facilitating cash handling, the system also supports visually impaired entrepreneurs and workers in informal sectors where digital payments are less prevalent. Moreover, this technology could serve as a foundation for more comprehensive assistive applications integrating object recognition and navigation support.

Future Work

Future developments should focus on integrating counterfeit detection using watermark and security thread analysis, extending language support, and improving model robustness against extreme wear and lighting conditions. Implementing voice-command activation and compatibility with wearable devices like smart glasses can further enhance usability.

Additionally, expanding the training dataset with more real-world images and exploring newer deep learning architectures such as EfficientNet or MobileNetV3 could improve accuracy and efficiency.

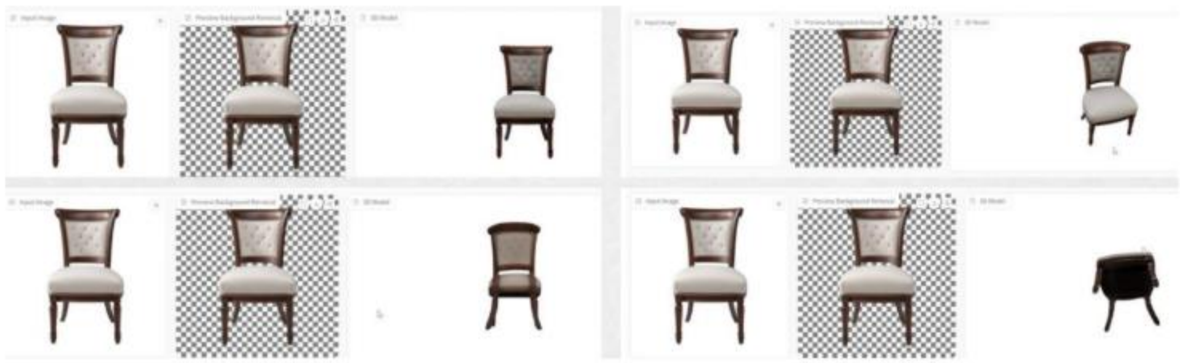

Fig 1: Working Model

CONCLUSION

The conversion of 2D images to 3D models is a vital and rapidly evolving field that bridges the gap between flat visual data and immersive three-dimensional representations. This technology has broad applications in entertainment, virtual and augmented reality, medical imaging, cultural heritage preservation, and industrial design, significantly enhancing how humans interact with digital content. Through the advancements in both classical computer vision techniques and modern deep learning methods, the ability to reconstruct detailed and accurate 3D models from 2D inputs has improved remarkably in recent years. Traditional approaches such as stereo vision, photogrammetry, and shape-from-shading laid the foundation for 3D reconstruction by using geometric principles and multi-view images. While effective in controlled environments, these methods often struggle with complex scenes, poor lighting, occlusions, and textureless surfaces. The advent of deep learning, especially convolutional neural networks (CNNs) and generative models, has transformed this landscape by enabling data-driven inference of depth and shape, even from a single 2D image. Deep learning models have demonstrated superior robustness and adaptability, allowing for more accurate, detailed, and faster reconstructions. However, challenges remain in the form of dataset limitations, handling reflective or transparent materials, occlusions, and real-time processing constraints, especially on mobile or embedded platforms. The hybrid integration of classical and learning-based methods presents a promising direction, combining the strengths of geometric constraints with the power of learned representations.

Looking forward, further research into self-supervised learning, multi-modal sensor fusion, and improved computational efficiency will continue to push the boundaries of 2D-to-3D conversion. Developing standardized benchmarks and datasets will also be crucial for consistent evaluation and progress in this domain. In conclusion, converting 2D images into 3D models unlocks vast potential for innovation across multiple industries, enhancing user experiences and enabling new possibilities in digital interaction. As this technology matures, it will become increasingly accessible, accurate, and versatile, ultimately contributing to more intuitive and immersive digital worlds.

REFERENCES

1. Reddy, C. N. K., & Murthy, G. V. (2012). Evaluation of Behavioral Security in Cloud Computing. *International Journal of Computer Science and Information Technologies*, *3*(2), 3328-3333.
2. Murthy, G. V., Kumar, C. P., & Kumar, V. V. (2017, December). Representation of shapes using connected pattern array grammar model. In *2017 IEEE Region 10 Humanitarian Technology Conference (R10-HTC)* (pp. 819-822). IEEE.
3. Krishna, K. V., Rao, M. V., & Murthy, G. V. (2017). Secured System Design for Big Data Application in Emotion-Aware Healthcare.
4. Rani, G. A., Krishna, V. R., & Murthy, G. V. (2017). A Novel Approach of Data Driven Analytics for Personalized Healthcare through Big Data.
5. Rao, M. V., Raju, K. S., Murthy, G. V., & Rani, B. K. (2020). Configure and Management of Internet of Things. *Data Engineering and Communication Technology*, 163.
6. Ramakrishna, C., Kumar, G. K., Reddy, A. M., & Ravi, P. (2018). A Survey on various IoT Attacks and its Countermeasures. *International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)*, *5*(4), 143-150.
7. Chithanuru, V., & Ramaiah, M. (2023). An anomaly detection on blockchain infrastructure using artificial intelligence techniques: Challenges and future directions–A review. *Concurrency and Computation: Practice and Experience*, *35*(22), e7724.
8. Prashanth, J. S., & Nandury, S. V. (2015, June). Cluster-based rendezvous points selection for reducing tour length of mobile element in WSN. In *2015 IEEE International Advance Computing Conference (IACC)* (pp. 1230-1235). IEEE.
9. Kumar, K. A., Pabboju, S., & Desai, N. M. S. (2014). Advance text steganography algorithms: an overview. *International Journal of Research and Applications*, *1*(1), 31-35.

10. Hnamte, V., & Balram, G. (2022). Implementation of Naive Bayes Classifier for Reducing DDoS Attacks in IoT Networks. *Journal of Algebraic Statistics*, *13*(2), 2749-2757.
11. Balram, G., Anitha, S., & Deshmukh, A. (2020, December). Utilization of renewable energy sources in generation and distribution optimization. In *IOP Conference Series: Materials Science and Engineering* (Vol. 981, No. 4, p. 042054). IOP Publishing.
12. Subrahmanyam, V., Sagar, M., Balram, G., Ramana, J. V., Tejaswi, S., & Mohammad, H. P. (2024, May). An Efficient Reliable Data Communication For Unmanned Air Vehicles (UAV) Enabled Industry Internet of Things (IIoT). In *2024 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT)* (pp. 1-4). IEEE.
13. Mahammad, F. S., Viswanatham, V. M., Tahseen, A., Devi, M. S., & Kumar, M. A. (2024, July). Key distribution scheme for preventing key reinstallation attack in wireless networks. In *AIP Conference Proceedings* (Vol. 3028, No. 1). AIP Publishing.
14. Lavanya, P. (2024). In-Cab Smart Guidance and support system for Dragline operator.
15. Kovoor, M., Durairaj, M., Karyakarte, M. S., Hussain, M. Z., Ashraf, M., & Maguluri, L. P. (2024). Sensor-enhanced wearables and automated analytics for injury prevention in sports. *Measurement: Sensors*, *32*, 101054.
16. Rao, N. R., Kovoor, M., Kishor Kumar, G. N., & Parameswari, D. V. L. (2023). Security and privacy in smart farming: challenges and opportunities. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*(7).
17. Madhuri, K. (2023). Security Threats and Detection Mechanisms in Machine Learning. *Handbook of Artificial Intelligence*, *255*.
18. Reddy, B. A., & Reddy, P. R. S. (2012). Effective data distribution techniques for multi-cloud storage in cloud computing. *CSE, Anurag Group of Institutions, Hyderabad, AP, India*.
19. Srilatha, P., Murthy, G. V., & Reddy, P. R. S. (2020). Integration of Assessment and Learning Platform in a Traditional Class Room Based Programming Course. *Journal of Engineering Education Transformations*, *33*, 179-184.
20. Reddy, P. R. S., & Ravindranadh, K. (2019). An exploration on privacy concerned secured data sharing techniques in cloud. *International Journal of Innovative Technology and Exploring Engineering*, *9*(1), 1190-1198.
21. Raj, R. S., & Raju, G. P. (2014, December). An approach for optimization of resource management in Hadoop. In *International Conference on Computing and Communication Technologies* (pp. 1-5). IEEE.
22. Ramana, A. V., Bhoga, U., Dhulipalla, R. K., Kiran, A., Chary, B. D., & Reddy, P. C. S. (2023, June). Abnormal Behavior Prediction in Elderly Persons Using Deep Learning. In *2023 International Conference on Computer, Electronics & Electrical Engineering & their Applications (IC2E3)* (pp. 1-5). IEEE.
23. Yakoob, S., Krishna Reddy, V., & Dastagiraiah, C. (2017). Multi User Authentication in Reliable Data Storage in Cloud. In *Computer Communication, Networking and Internet Security: Proceedings of IC3T 2016* (pp. 531-539). Springer Singapore.
24. Sukhavasi, V., Kulkarni, S., Raghavendran, V., Dastagiraiah, C., Apat, S. K., & Reddy, P. C. S. (2024). Malignancy Detection in Lung and Colon Histopathology Images by Transfer Learning with Class Selective Image Processing.
25. Dastagiraiah, C., Krishna Reddy, V., & Pandurangarao, K. V. (2018). Dynamic load balancing environment in cloud computing based on VM ware off-loading. In *Data Engineering and Intelligent Computing: Proceedings of IC3T 2016* (pp. 483-492). Springer Singapore.
26. Swapna, N. (2017). „Analysis of Machine Learning Algorithms to Protect from Phishing in Web Data Mining". *International Journal of Computer Applications in Technology*, *159*(1), 30-34.
27. Moparthi, N. R., Bhattacharyya, D., Balakrishna, G., & Prashanth, J. S. (2021). Paddy leaf disease detection using CNN.
28. Balakrishna, G., & Babu, C. S. (2013). Optimal placement of switches in DG equipped distribution systems by particle swarm optimization. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, *2*(12), 6234-6240.
29. Moparthi, N. R., Sagar, P. V., & Balakrishna, G. (2020, July). Usage for inside design by AR and VR technology. In *2020 7th International Conference on Smart Structures and Systems (ICSSS)* (pp. 1-4). IEEE.

30. Amarnadh, V., & Moparthi, N. R. (2023). Comprehensive review of different artificial intelligence-based methods for credit risk assessment in data science. *Intelligent Decision Technologies*, *17*(4), 1265-1282.
31. Amarnadh, V., & Moparthi, N. (2023). Data Science in Banking Sector: Comprehensive Review of Advanced Learning Methods for Credit Risk Assessment. *International Journal of Computing and Digital Systems*, *14*(1), 1-xx.
32. Amarnadh, V., & Rao, M. N. (2025). A Consensus Blockchain-Based Credit Risk Evaluation and Credit Data Storage Using Novel Deep Learning Approach. *Computational Economics*, 1-34.
33. Shailaja, K., & Anuradha, B. (2017). Improved face recognition using a modified PSO based self-weighted linear collaborative discriminant regression classification. *J. Eng. Appl. Sci*, *12*, 7234-7241.
34. Sekhar, P. R., & Goud, S. (2024). Collaborative Learning Techniques in Python Programming: A Case Study with CSE Students at Anurag University. *Journal of Engineering Education Transformations*, *38*.
35. Sekhar, P. R., & Sujatha, B. (2023). Feature extraction and independent subset generation using genetic algorithm for improved classification. *Int. J. Intell. Syst. Appl. Eng*, *11*, 503-512.
36. Pesaramelli, R. S., & Sujatha, B. (2024, March). Principle correlated feature extraction using differential evolution for improved classification. In *AIP Conference Proceedings* (Vol. 2919, No. 1). AIP Publishing.
37. Tejaswi, S., Sivaprashanth, J., Bala Krishna, G., Sridevi, M., & Rawat, S. S. (2023, December). Smart Dustbin Using IoT. In *International Conference on Advances in Computational Intelligence and Informatics* (pp. 257-265). Singapore: Springer Nature Singapore.
38. Moreb, M., Mohammed, T. A., & Bayat, O. (2020). A novel software engineering approach toward using machine learning for improving the efficiency of health systems. *IEEE Access*, *8*, 23169-23178.
39. Ravi, P., Haritha, D., & Niranjan, P. (2018). A Survey: Computing Iceberg Queries. *International Journal of Engineering & Technology*, *7*(2.7), 791-793.
40. Madar, B., Kumar, G. K., & Ramakrishna, C. (2017). Captcha breaking using segmentation and morphological operations. *International Journal of Computer Applications*, *166*(4), 34-38.
41. Rani, M. S., & Geetavani, B. (2017, May). Design and analysis for improving reliability and accuracy of big-data based peripheral control through IoT. In *2017 International Conference on Trends in Electronics and Informatics (ICEI)* (pp. 749-753). IEEE.
42. Reddy, T., Prasad, T. S. D., Swetha, S., Nirmala, G., & Ram, P. (2018). A study on antiplatelets and anticoagulants utilisation in a tertiary care hospital. *International Journal of Pharmaceutical and Clinical Research*, *10*, 155-161.
43. Prasad, P. S., & Rao, S. K. M. (2017). HIASA: Hybrid improved artificial bee colony and simulated annealing based attack detection algorithm in mobile ad-hoc networks (MANETs). *Bonfring International Journal of Industrial Engineering and Management Science*, *7*(2), 01-12.
44. AC, R., Chowdary Kakarla, P., Simha PJ, V., & Mohan, N. (2022). Implementation of Tiny Machine Learning Models on Arduino 33–BLE for Gesture and Speech Recognition.
45. Subrahmanyam, V., Sagar, M., Balram, G., Ramana, J. V., Tejaswi, S., & Mohammad, H. P. (2024, May). An Efficient Reliable Data Communication For Unmanned Air Vehicles (UAV) Enabled Industry Internet of Things (IIoT). In *2024 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT)* (pp. 1-4). IEEE.
46. Nagaraj, P., Prasad, A. K., Narsimha, V. B., & Sujatha, B. (2022). Swine flu detection and location using machine learning techniques and GIS. *International Journal of Advanced Computer Science and Applications*, *13*(9).
47. Priyanka, J. H., & Parveen, N. (2024). DeepSkillNER: an automatic screening and ranking of resumes using hybrid deep learning and enhanced spectral clustering approach. *Multimedia Tools and Applications*, *83*(16), 47503-47530.
48. Sathish, S., Thangavel, K., & Boopathi, S. (2010). Performance analysis of DSR, AODV, FSR and ZRP routing protocols in MANET. *MES Journal of Technology and Management*, 57-61.
49. Siva Prasad, B. V. V., Mandapati, S., Kumar Ramasamy, L., Boddu, R., Reddy, P., & Suresh Kumar, B. (2023). Ensemble-based cryptography for soldiers' health monitoring using mobile ad hoc networks. *Automatika: časopis za automatiku, mjerenje, elektroniku, računarstvo i komunikacije*, *64*(3), 658-671.

50. Elechi, P., & Onu, K. E. (2022). Unmanned Aerial Vehicle Cellular Communication Operating in Non-terrestrial Networks. In *Unmanned Aerial Vehicle Cellular Communications* (pp. 225-251). Cham: Springer International Publishing.
51. Prasad, B. V. V. S., Mandapati, S., Haritha, B., & Begum, M. J. (2020, August). Enhanced Security for the authentication of Digital Signature from the key generated by the CSTRNG method. In *2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT)* (pp. 1088-1093). IEEE.
52. Mukiri, R. R., Kumar, B. S., & Prasad, B. V. V. (2019, February). Effective Data Collaborative Strain Using RecTree Algorithm. In *Proceedings of International Conference on Sustainable Computing in Science, Technology and Management (SUSCOM), Amity University Rajasthan, Jaipur-India*.
53. Balaraju, J., Raj, M. G., & Murthy, C. S. (2019). Fuzzy-FMEA risk evaluation approach for LHD machine–A case study. *Journal of Sustainable Mining, 18*(4), 257-268.
54. Thirumoorthi, P., Deepika, S., & Yadaiah, N. (2014, March). Solar energy based dynamic sag compensator. In *2014 International Conference on Green Computing Communication and Electrical Engineering (ICGCCEE)* (pp. 1-6). IEEE.
55. Vinayasree, P., & Reddy, A. M. (2025). A Reliable and Secure Permissioned Blockchain-Assisted Data Transfer Mechanism in Healthcare-Based Cyber-Physical Systems. *Concurrency and Computation: Practice and Experience*, *37*(3), e8378.
56. Acharjee, P. B., Kumar, M., Krishna, G., Raminenei, K., Ibrahim, R. K., & Alazzam, M. B. (2023, May). Securing International Law Against Cyber Attacks through Blockchain Integration. In *2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)* (pp. 2676-2681). IEEE.
57. Ramineni, K., Reddy, L. K. K., Ramana, T. V., & Rajesh, V. (2023, July). Classification of Skin Cancer Using Integrated Methodology. In *International Conference on Data Science and Applications* (pp. 105-118). Singapore: Springer Nature Singapore.
58. LAASSIRI, J., EL HAJJI, S. A. Ï. D., BOUHDADI, M., AOUDE, M. A., JAGADISH, H. P., LOHIT, M. K., ... & KHOLLADI, M. (2010). Specifying Behavioral Concepts by engineering language of RM-ODP. *Journal of Theoretical and Applied Information Technology*, *15*(1).
59. Prasad, D. V. R., & Mohanji, Y. K. V. (2021). FACE RECOGNITION-BASED LECTURE ATTENDANCE SYSTEM: A SURVEY PAPER. *Elementary Education Online*, *20*(4), 1245-1245.
60. Dasu, V. R. P., & Gujjari, B. (2015). Technology-Enhanced Learning Through ICT Tools Using Aakash Tablet. In *Proceedings of the International Conference on Transformations in Engineering Education: ICTIEE 2014* (pp. 203-216). Springer India.
61. Reddy, A. M., Reddy, K. S., Jayaram, M., Venkata Maha Lakshmi, N., Aluvalu, R., Mahesh, T. R., ... & Stalin Alex, D. (2022). An efficient multilevel thresholding scheme for heart image segmentation using a hybrid generalized adversarial network. *Journal of Sensors*, *2022*(1), 4093658.
62. Srinivasa Reddy, K., Suneela, B., Inthiyaz, S., Hasane Ahammad, S., Kumar, G. N. S., & Mallikarjuna Reddy, A. (2019). Texture filtration module under stabilization via random forest optimization methodology. *International Journal of Advanced Trends in Computer Science and Engineering*, *8*(3), 458-469.
63. Ramakrishna, C., Kumar, G. K., Reddy, A. M., & Ravi, P. (2018). A Survey on various IoT Attacks and its Countermeasures. *International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)*, *5*(4), 143-150.
64. Sirisha, G., & Reddy, A. M. (2018, September). Smart healthcare analysis and therapy for voice disorder using cloud and edge computing. In *2018 4th international conference on applied and theoretical computing and communication technology (iCATccT)* (pp. 103-106). IEEE.
65. Reddy, A. M., Yarlagadda, S., & Akkinen, H. (2021). An extensive analytical approach on human resources using random forest algorithm. *arXiv preprint arXiv:2105.07855*.
66. Kumar, G. N., Bhavanam, S. N., & Midasala, V. (2014). Image Hiding in a Video-based on DWT & LSB Algorithm. In *ICPVS Conference*.
67. Naveen Kumar, G. S., & Reddy, V. S. K. (2022). High performance algorithm for content-based video retrieval using multiple features. In *Intelligent Systems and Sustainable Computing: Proceedings of ICISSC 2021* (pp. 637-646). Singapore: Springer Nature Singapore.
68. Reddy, P. S., Kumar, G. N., Ritish, B., SaiSwetha, C., & Abhilash, K. B. (2013). Intelligent parking space detection system based on image segmentation. *Int J Sci Res Dev*, *1*(6), 1310-1312.

69. Naveen Kumar, G. S., Reddy, V. S. K., & Kumar, S. S. (2018). High-performance video retrieval based on spatio-temporal features. *Microelectronics, Electromagnetics and Telecommunications*, 433-441.
70. Kumar, G. N., & Reddy, M. A. BWT & LSB algorithm based hiding an image into a video. *IJESAT*, 170-174.
71. 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.
72. 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.
73. 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.
74. 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.
75. 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.
76. 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.
77. 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.
78. 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.
79. 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.
80. Praveen, R. V. S. (2024). *Data Engineering for Modern Applications*. Addition Publishing House.