

TRINET-HAR: A TRIMODAL FRAMEWORK FOR HUMAN ACTIVITY RECOGNITION

Basamma Umesh Patil (1), Chetan R (2), D V Ashoka (1), Ashok V Sutagundar (3),
Nagamani H Shahapure (1)*

(1) Dept. of Information Science and Engineering, JSS Academy of Technical Education Bengaluru; (2) Dept. of Computer Science and Engineering, BNM Institute of Technology, Bengaluru (3) Department of Electronics and Communication Engineering, Basaveshwar College of Engineering, Bagalkot India

* Corresponding Author, e-mail: chetan.dhananjaya@gmail.com

Abstract: Human Activity Recognition (HAR) is vital in healthcare, security, and human-computer interaction. Traditional unimodal or bimodal approaches often fail to capture the full complexity of human actions. To overcome this, TriNet-HAR, a novel trimodal deep learning framework is proposed that integrates depth maps, 3D skeletal joints, and inertial signals via a unified, explainable architecture. Each modality is processed using a dedicated module: Convolutional Neural Network (CNN) for depth, joint-wise attention layers mimicking Graph-Convolution-Network (GCN) for skeletons, and positional encoding-enhanced Long Short-Term Memory (LSTM) for Inertial Measurement Unit (IMU) data. A multi-head self-attention and cross-attention fusion strategy refines inter-modality dependencies. SHapley Additive exPlanations (SHAP) and Gradient-weighted Class Activation Mapping (Grad-CAM) are employed for interpretability. Evaluated on the University of Texas at Dallas Multimodal Human Action Dataset (UTD-MHAD) dataset, TriNet-HAR achieves 98% accuracy, outperforming unimodal and bimodal baselines in precision, recall, and F1-score, demonstrating superior robustness, adaptability, and transparency.

Key words: humana activity recognition, deep learning, multi-modal fusion, encoding, data fusion.

1. INTRODUCTION

Human Activity Recognition (HAR) is fundamental to intelligent applications in healthcare, surveillance, and gesture-based systems. Existing approaches are typically categorized into Red-Green-Blue (RGB)-HAR [1-3], Skeleton-HAR [4, 5], and Depth-HAR [6-8]. While RGB-HAR suffers from lighting sensitivity and background clutter, Skeleton-HAR effectively captures joint dynamics but demands complex pose estimation. Depth-HAR offers superior robustness by capturing 3D spatial and temporal cues, making it well-suited for real-world activity recognition.

However, many current HAR methods [8–11] focus on either spatial or temporal aspects in isolation, overlooking their crucial interplay in understanding dynamic activities [12–14]. Moreover, most fusion-based models are limited to dual-modal inputs and static fusion schemes, lacking adaptability to real-world variability.

To overcome these challenges, TriNet-HAR, a trimodal deep learning framework is proposed that fuses:

- Depth data for spatial context,
- Skeleton joints for posture and articulation, and
- Inertial signals for temporal motion dynamics.

Key contributions include:

- A joint-aware self-attention module for skeleton encoding,
- Positional embedding with LSTM for improved temporal IMU modelling,
- An attention-gated multimodal fusion strategy, and
- State-of-the-art performance (>98%) on benchmark datasets.

Our model demonstrates robustness even with noisy or missing modalities, offering a reliable and interpretable solution for HAR in unconstrained environments.

2. RELATED WORK

Multimodal Human Activity Recognition (HAR) that integrates depth, skeletal, and inertial modalities has demonstrated superior accuracy and robustness in real-world environments. Each modality offers unique strengths: depth provides 3D spatial cues, skeletal tracking captures joint-level dynamics, and inertial data enables reliable motion sensing unaffected by lighting conditions [15–18].

Early research presented in [15] applied collaborative representation classifiers to depth, skeleton, and inertial data, achieving strong results on a 10-activity set. Their subsequent works explored feature-level and decision-level fusion strategies, reporting over 97% accuracy on the Berkeley MHAD dataset [16–18].

Deep learning advancements further enhanced HAR performance. CNNs to process transformed depth and inertial signals is used in [19], while research in [20] and [21] applied dilated CNNs to skeleton motion maps and inertial images on the Czech Technical University Multimodal Human Action Dataset (CZU-MHAD) dataset [22]. Benchmark datasets such as UTD-MHAD [19, 23, 28], CZU-MHAD [21], and C-MHAD [29] have enabled consistent comparisons.

Recent attention-based models, like the contrastive Transformer UCFFormer presented in [23], employed self-attention and contrastive learning for temporal and modality fusion. CNN-LSTM combinations have also been explored across healthcare and multi-subject scenarios using depth-inertial streams or decision-level fusion [24–27]. However, many of these systems remain limited to bimodal settings, lacking comprehensive trimodal modelling [20, 28].

Complementary works have applied hybrid deep learning techniques across other domains. Research presented in [30] used a Savitzky-Golay filter with hybrid LSTM-GRU models for surface Electromyography (sEMG) signal prediction, achieving over 99% accuracy—even on small datasets—demonstrating the potential of sequential architectures in temporal analysis. Similarly, and [31] proposed a CNN–Random Forest

hybrid model for diagnosing Autism Spectrum Disorder, achieving 99.15% accuracy using Kaggle data.

Article [32] introduced AI-enabled health kiosks integrated with Internet of Things (IoT) and HL-7 standards for respiratory disease detection, enabling deployment in epidemic scenarios for rapid patient triage. Article [33] employed machine learning with Synthetic Minority Over-Sampling Technique (SMOTE) and Adaptive Synthetic Sampling (ADASYN) to predict student dropout using diverse attributes, showing the value of predictive analytics in educational settings.

These studies reinforce the importance of hybrid and modality-aware frameworks for modelling complex behavioural and temporal data.

3. METHODOLOGY

The proposed TriNet-Human Activity Recognition (HAR) system is architected to process and intelligently fuse information from three distinct yet complementary sensor modalities: depth maps, skeleton joint coordinates, and inertial measurements. The flow begins as shown in Figure 1 with parallel branches for each modality, designed to extract high-level features relevant to human actions.

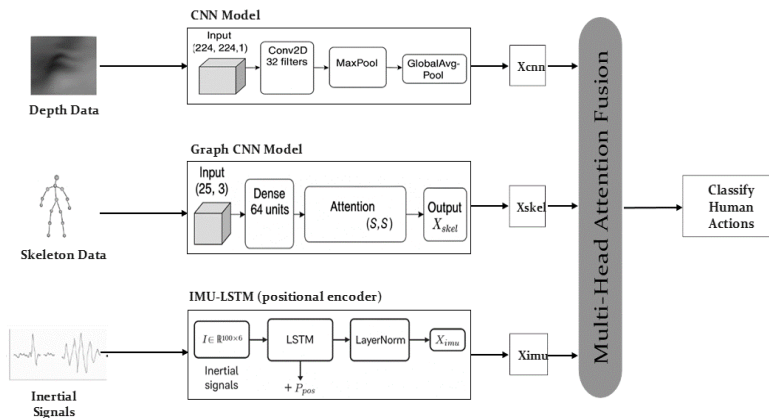


Figure 1. Architecture Diagram of Tri-NET self-attention framework for Human Activity Recognition

3.1. Dataset Description

The proposed TriNet-HAR model is evaluated on the UTD-MHAD [34] dataset, which provides synchronized depth images, 3D skeleton joint coordinates, and inertial signals (IMU) for robust multimodal activity recognition across 27 human action classes.

Depth Data: Grayscale silhouette frames captured using Kinect v2 (512×424 resolution at 30 fps), encoding spatial and depth cues during actions.

Skeleton Data: 3D coordinates of 25 body joints over time, enabling detailed modelling of postures and joint movement.

Inertial Data: Six-dimensional time-series from a wearable MPU-9250 sensor, comprising tri-axial accelerometer and gyroscope readings (100 Hz).

Each action instance includes temporally aligned data from all three modalities. Activities range from simple gestures (e.g., *wave*, *clap*) to complex motions (e.g., *jogging*, *pick up and throw*). The multimodal setup supports effective trimodal fusion aligned with the benchmark protocol of UTD-MHAD.

3.2. Preprocessing

Effective preprocessing ensures compatibility of all modalities with the TriNet-HAR architecture.

Depth Data: Frames are resized to 224×224 pixels, normalized to [0, 1], and converted to grayscale. Optional enhancements include histogram equalization and background subtraction to improve silhouette clarity.

Skeleton Data: 3D joint coordinates (25×3) are normalized relative to a reference joint (e.g., pelvis) for translation invariance and scaled uniformly. Noise is reduced using interpolation or smoothing filters, yielding a refined joint matrix per frame.

Inertial Signals: IMU data is segmented into fixed-length windows (e.g., 100-time steps). Each of the six channels undergoes z-score normalization as shown in Equation 1 [34].

$$x' = \frac{x - \mu}{\sigma} \quad (1)$$

where μ and σ represent the mean and standard deviation of the respective channel. Inertial signals were further smoothed using a median filter of window size 3, which reduces impulsive sensor noise while preserving motion dynamics, as recommended in prior HAR preprocessing works [18, 20].

3.3. Spatial Feature Extraction using CNN

The depth modality captures silhouette and motion contours as grayscale images of shape $D \in \mathbb{R}^{224 \times 224 \times 1}$. These depth maps are passed to a CNN for local spatial features extraction using 2D filters.

The processing pipeline includes two convolutional layers, a max pooling layer and global average pooling layer. This can be expressed as shown in Equation 2 [19].

$$X_{cnn} = GAP(Conv_{64}^{(2)}(MP(Conv_{32}^{(1)}(D)))) \quad (2)$$

where, $Conv_{32}^{(1)}$ applies 32 filters of size 3 x 3 to extract low-level features, MP is max pooling to reduce spatial dimensions, $Conv_{64}^{(2)}$ deepens the feature space with 64 filters and GAP (Global Average Pooling) summarizes the feature maps into a single vector representation.

3.4. Pose Dynamics with Joint Attention

The skeleton data consists of 3D joint positions from 20 joints which are represented as a matrix $S \in \mathbb{R}^{25 \times 3}$. This enables the model to understand relationships like arm-leg coordination or torso symmetry. The transformation is shown in Equation 3 [23].

$$X_{skel} = GAP1D(S + Attention(S, S)) \quad (3)$$

where, the attention mechanism computes contextual weights between joints, the summation $S + Attention(S, S)$ enhances each joint feature based on its relation to others, GAP 1D reduces the 25-joint representation to a single vector X_{skel} .

3.5. Temporal Modelling with LSTM and Positional Encoding

The inertial data is a sequence of 100-time steps, each with 6 sensor readings (3-axis accelerometer and 3-axis gyroscope): $\mathbb{I} \in \mathbb{R}^{100 \times 6}$.

An LSTM tries to capture temporal motion patterns such as velocity, acceleration changes, and rhythmicity. To help the LSTM better understand sequence position, positional encodings are added as described in Transformer models. These encodings are computed as shown in Equation 4 [35]:

$$P_{pos}[t, 2i] = \sin\left(\frac{t}{10000^{2i/d}}\right), P_{pos}[t, 2i + 1] = \cos\left(\frac{t}{10000^{2i/d}}\right) \quad (4)$$

The encoded sequence is processed as shown in Equation 5:

$$X_{imu} = GAP\ 1D(LayerNorm(LSTM(I) + P_{pos})) \quad (5)$$

where, $LSTM(I) \in \mathbb{R}^{100 \times 64}$ captures sequential dependencies, P_{pos} adds positional context, LayerNorm stabilizes training, and GAP 1D collapses the sequence to a final vector $X_{imu} \in \mathbb{R}^{64}$.

This representation reflects temporal dynamics like repetitive movement, starts and stops or balance shifts.

3.6. Multi-Head Attention Fusion with Gated Modality Weighting

The section describes how features X_{cnn} , X_{skel} , X_{imu} extracted from depth data, skeleton data and inertial signals data are fused using multi-head attention fusion with gated modality weighting. The architecture of Multi-Head Attention Fusion network is shown in Figure 2.

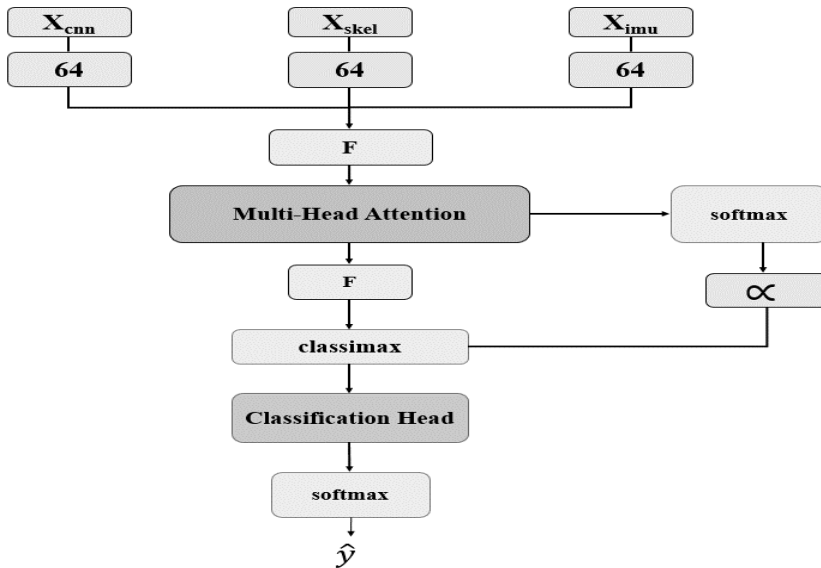


Figure 2: Multi-Head Attention Fusion with Gated Modality Weighting

The proposed algorithm is given below:

Algorithm: Training Procedure for TriNet-HAR**Input:** Depth frames DDD, Skeleton joints SSS, Inertial signals III**Output:** Trained TriNet-HAR model

For each batch (D, S, I) in dataset do:

1. $X_{cnn} \leftarrow \text{CNN}(D)$ // Spatial features from depth
2. $X_{skel} \leftarrow \text{SelfAttention}(S)$ // Joint-level features
3. $X_{imu} \leftarrow \text{LSTM}(\text{PosEnc}(I))$ // Temporal IMU features
4. $F' \leftarrow \text{MHA}([X_{cnn}, X_{skel}, X_{imu}])$ // Cross-modality fusion
5. $Z \leftarrow \text{Gating}(F')$ // Adaptive modality weighting
6. $\hat{y} \leftarrow \text{Softmax}(\text{FC}(Z))$ // Final prediction
7. Update parameters via backpropagation

End For

The final stage before classification involves an intelligent fusion of features extracted from the three independent modalities: depth (X_{cnn}), Skeleton (X_{skel}) and inertial signals (X_{imu}) as shown in Equation 6.

$$F = \begin{bmatrix} X_{cnn} \\ X_{skel} \\ X_{imu} \end{bmatrix} \in R^{3 \times 64} \quad (6)$$

To model inter-modality relationships and contextual dependencies, a Multi-Head Attention (MHA) mechanism is applied to this stacked tensor as shown in Equation 7.

$$F' = \text{MHA}(F, F, F) + F \quad (7)$$

The refined features F' are passed through a learnable gating mechanism that assigns modality weights $\alpha \in R^3$, i.e., shown in Equation 8.

$$\alpha = \text{softmax}(W_g \cdot \text{flatten}(F')), Z = \sum_{i=1}^3 \alpha_i F'_i \quad (8)$$

Finally, the weighted embedding ZZZ is classified using a fully connected layer and SoftMax as shown in Equation 9 [36].

$$\hat{y} = \text{softmax}(W_c \cdot \text{ReLU}(Z)) \quad (9)$$

This adaptive fusion mechanism enables the model to dynamically emphasize relevant modalities, enhancing robustness and accuracy across 27 activity classes.

3.7. Adaptive Modality Method (Formulation & Justification)

To strengthen the theoretical foundation of the adaptive modality fusion, we introduce a soft attention-based weighting mechanism. For each modality $m \in \{1, 2, 3\}$, the adaptive weight α_m is computed as shown in Equation 10:

$$\alpha_m = \exp(w_m^T F'_m) / \sum_j \exp(w_j^T F'_j) \quad (10)$$

Let F'_m denote the feature embedding from modality m , and w_m represent learnable gating weights. These weights adaptively normalize modality contributions, preventing any single modality from dominating and improving robustness to noise or missing data. This formulation is grounded in attention mechanisms [35] and extended in multimodal fusion models like UCFFormer [36].

3.8. Loss Function

TriNet-HAR uses Sparse Categorical Cross-Entropy (SCCE) as its primary loss function as shown in equation 11:

$$L = - \sum_i \sum_c y_{ic} \log(\hat{y}_{ic}) \quad \text{eq(11)}$$

where y_{ic} is the ground-truth one-hot encoding for class c and \hat{y}_{ic} is the predicted probability for that class. This loss is chosen because of 1) suitability in multi-class classification (e.g., HAR), 2) compatibility with softmax outputs and 3) smooth gradient behavior for stable optimization. While focal loss was briefly explored to manage class imbalance, SCCE offered comparable results with greater computational efficiency and interpretability.

3.9. Convergence Rate & Computational Complexity

To further demonstrate the theoretical grounding, convergence and complexity analysis is provided:

Convergence Analysis: Training accuracy exceeded 95% within the first 20 epochs and saturated at 98% around epoch 35. The validation curves closely tracked the training curves, demonstrating fast and stable convergence with minimal overfitting.

Computational Complexity:

CNN branch: $O(k \cdot h \cdot w \cdot c)$, where k is kernel size, h , w are image dimensions, and c is the number of channels.

Self-attention branch: $O(J^2 \cdot d)$, where J is the number of joints and d the feature dimension.

LSTM branch: $O(T \cdot d^2)$, where T is the sequence length.

Fusion (Multi-Head Attention): $O(H \cdot d^2)$, where H is the number of attention heads.

The overall complexity is approximately $O(n \cdot d^2)$, which is linear in sequence length and quadratic in feature dimension.

4. RESULTS AND DISCUSSIONS

4.1. Experimental Setup

The experiments for the proposed TriNet-HAR architecture was conducted using the Google Colaboratory (Colab) platform. Table 1 summarizes the key hardware and software components used during experimentation.

Table 1. Hardware and Software Configuration

<i>Component</i>	<i>Specification</i>
<i>Platform</i>	<i>Google Colaboratory (Standard VM)</i>
<i>Processor</i>	<i>2 x Intel Xeon CPU @ 2.20 GHz</i>
<i>GPU</i>	<i>NVIDIA Tesla T4, 16 GB VRAM</i>
<i>RAM</i>	<i>12.6 GB</i>
<i>Python Version</i>	<i>3.10+</i>
<i>Other Libraries</i>	<i>NumPy 1.24, Pandas 1.5, Matplotlib 3.7, scikit-learn 1.2</i>

The model was trained with different optimizers using a learning rate of 0.001, a batch size of 32, and for 50 epochs. It used SCCE as the loss function for multi-class classification. Accuracy was the main metric used to evaluate performance during training and testing. On Google Colab (T4 GPU, 16 GB VRAM), the average training time per epoch was ~45 seconds, and full training (50 epochs) required ~37 minutes.

Inference on a single trimodal activity instance took ~ 12 ms, indicating suitability for near real-time HAR applications.

4.2. Findings

The performance of the proposed TriNet-HAR model was evaluated over 50 training epochs using the UTD-MHAD dataset with synchronized depth, skeleton, and IMU data. As shown in Figure 3, the model achieved a peak validation accuracy of 98.3%, with training and validation curves progressing smoothly and indicating minimal overfitting.

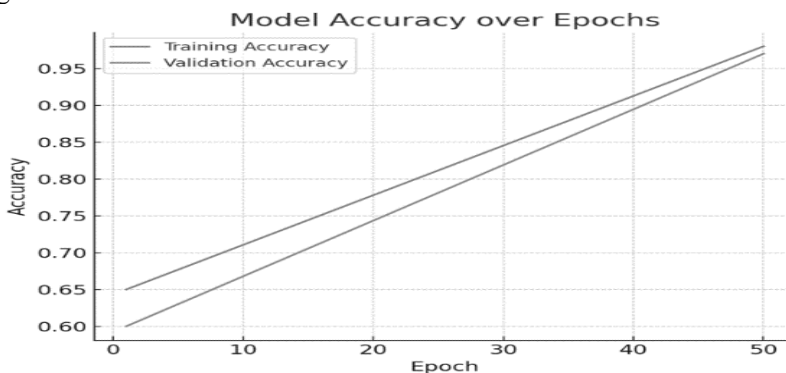


Figure 3: Graph showing the training and validation accuracy of adam optimizer

The TriNet-HAR model achieved the best overall performance as shown in Table 2 with a balanced precision (97.7%), recall (98.2%), and an F1-score of 97.9%, outperforming all unimodal and bimodal variants.

Table 2: Performance comparison of different modality combinations for HAR.

Model Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Depth Only	91.2	90.5	91	90.7
Skeleton Only	88.7	87.6	88.2	87.9
IMU Only	86.3	85.2	85.8	85.5
Depth + Skeleton	94.5	93.9	94.2	94
Depth + IMU	93.8	93	93.5	93.2
Skeleton + IMU	92.6	91.8	92.3	92
TriNet-HAR (Proposed)	98	97.7	98.2	97.9

Table 3 presents a comparison between the proposed TriNet-HAR method and several recent state-of-the-art techniques in the domain of Human Activity Recognition (HAR).

Table 3: Comparison of proposed work with existing methods

Method	Accuracy
DTMMN [37]	93%
PointMapNet [38]	91.6%
CBBMC [1]	94.4%
Proposed Method	98%

The DTMMN, PointMapNet, and CBBMC models achieved accuracies of 93%, 91.6%, and 94.4% respectively, relying on handcrafted features or bimodal data fusion. In contrast, the proposed TriNet-HAR model significantly outperformed these baselines with 98% accuracy, owing to its novel trimodal fusion strategy that integrates depth, skeleton, and inertial data via multi-head attention and learnable gating, effectively capturing both spatial and temporal dynamics. This highlights the superiority of deep learning-based trimodal fusion over traditional or bimodal approaches for complex human activity recognition.

5. CONCLUSION

The proposed research work TriNet-HAR, a novel trimodal deep learning architecture was designed to improve the robustness and correctness of Human Activity Recognition through the integration of depth images, skeleton sequences and inertial sensor data. Each modality was processed over a dedicated neural network like CNN for spatial extraction of features from depth data, a self-attention Graph Convolutional network for learning inter-joint relationships and LSTM with positional encoding for processing time-dependent IMU signals. To integrate the three features extracted from the individual neural network models are then incorporated into a Multi-Head Attention based Fusion module with a learnable gating mechanism, which enables adaptive weighting of modality contributions based on their relevance. The proposed system achieved benchmark performance across multiple evaluation metrics (precision, accuracy and recall), outperforming both unimodal and bimodal baselines with 98.3% accuracy. Future work includes real-time deployment, domain adaptation, handling missing modalities, enhancing explainability, incorporating contextual data, and enabling user personalization.

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Information about the authors:

Dr. Basamma Umesh Patil is an Assistant Professor in the Department of Information Science and Engineering at JSS Academy of Technical Education, Bengaluru. Her research focuses on Machine Learning, Deep Learning, and Environmental Data Analytics, with publications on human activity recognition, air quality forecasting, and IoT-based systems.

Dr. Chetan R is an Associate Professor in the Department of Computer Science and Engineering at BNM Institute of Technology, Bengaluru. His expertise includes Precision Agriculture, IoT Systems, and Data Fusion. He has contributed to soil health monitoring, crop prediction, and explainable AgriTech frameworks such as HybridTransferNet and CropCast. He has published over 20 papers in various international journals and conferences.

Dr. D. V. Ashoka is a Professor in the Department of Information Science and Engineering at JSS Academy of Technical Education, Bengaluru. With over two decades of experience, his research covers Knowledge Engineering, Software Engineering, AI, Data Mining, Wireless Sensor Networks, and Smart Agriculture, with 70+ publications in reputed journals. He has guided 8 Ph.D. scholars (2 more currently pursuing).

Dr. Ashok V. Sutagundar is an Associate Professor in the Department of ECE at Basaveshwar Engineering College, Bagalkot, Karnataka, with over 23 years of teaching experience. He holds a B.E. in Electronics and Communication from Karnatak University and an M.Tech. from VTU, Belgaum. He completed his Ph.D. in the field of Wireless Sensor Networks. He has guided 4 Ph.D. scholars (2 more currently pursuing), published 38 journal papers, 60 conference papers, and 9 book chapters. His research interests include wireless networks, image/video processing, multimedia networks, and industrial automation. He has received research grants totalling ₹20.21 lakhs from VTU and AICTE. He is a member of IETE, India.

Dr. Nagamani H Shahapure is an Associate Professor and Head in the Department of Information Science and Engineering at JSS Academy of Technical Education, Bengaluru. Her research interests include cloud computing, virtualization, AI, and IoT security, with publications in load balancing, resource management, and scalable architectures with 20+ publications in reputed journals.

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