ISSN: 2584-0495 Vol. 3, Issue 3, pp. 1599-1604

International Journal of Microsystems and IoT

ISSN: (Online) Journal homepage: https://www.ijmit.org

Pipelined Multilayer AI-Based Point-of-Care Model for Diagnosis of Spinal Cord Disorders in Big Clinical Data

Kanchan Bala, Modal Kumari, Anju Kumari, Anamika Kumari and Gajala Praveen

Cite as: Bala, K., Kumari, M., Kumari, A., Kumari, A., & Praveen, G. (2025). Soil Analysis and Moisture Prediction Using Machine Learning: A Review. International Journal of Microsystems and IoT, 3(3), 1599–1604. https://doi.org/10.5281/zenodo.18146028

Published online: 10 March 2025

https://doi.org/10.5281/zenodo.18146028

International Journal of Microsystems and IoT
Vol.3, Issue 3, pp.1599-1604; DOI: https://doi.org/10.5281/zenodo.18146028

Check for updates

Soil Analysis and Moisture Prediction Using Machine Learning: A Review

Kanchan Bala, Modal Kumari, Anju Kumari, Anamika Kumari and Gajala Praveen

Department of Computer Science & Engineering, Gaya College of Engineering, Gaya, Bihar

ABSTRACT
This India's agricultural sector employs the most people. Agricultural engagement reports for around 60% of India's population and 18% of its GDP. Low production is due to a absence of research in this industry. Waterlogging, soil erosion, nitrogen shortage, and other issues drive Indian agricultural land. Computational research and machine learning play a important role in advancing the agricultural industry. Different scientific and technological researcher has been performed on soil moisture prediction. Numerous methodologies have been proposed for addressing this challenge, including deep learning, machine learning, Internet of Things (IoT), statistical approaches, and image processing techniques. This paper presents a comprehensive survey of various research works focused on soil moisture prediction utilizing soft computing, data mining machine and learning, techniques. These include support vector machines, neural networks, rough set theory, fuzzy logic, k-means clustering, genetic algorithms, and K-NN (k-nearest neighbors). Additionally, this paper presents existing works and suggestions for future research directions.

KEYWORDS
Soil Moisture, Soft Computing, Prediction, Neural Network, Data Mining Convolutional Neural Network, Machine Learning,

1. INTRODUCTION

A country's overall progress with other nations is primarily determined by its agricultural sector. It is the way of life in a place like India. Agriculture remains one of the primary fields where technical developments are highly valued, even in the era of technology. Farmers can increase crop output and apply fertilizers in the correct amounts by having a precise understanding of the soil's nutrient composition. As a result, soil nutrient analysis has become essential in agriculture. Machine learning approaches significantly improve the speed and precision of agricultural analysis.

Machine learning-powered smart farming, with its high-precision algorithms. It involves image processing for crop quality identification, various algorithms for crop production prediction, sensors and algorithms for monitoring field conditions, and disease detection, including crop, soil, and water management, consistently producing useful outcomes. Soil moisture is a critical factor in agriculture, directly affecting crop growth, irrigation efficiency, and overall farm productivity. Traditional soil moisture prediction methods, like gravimetric analysis and time-domain reflectometry (TDR), can be limited in spatial coverage, labor-intensive, and expensive.

Therefore, machine learning (ML) techniques have been proposed to accurately and efficiently predict soil moisture levels, thereby overcoming the challenges of traditional methods. The model will integrate multiple data sources, including IoT-based soil sensors, meteorological data and remote sensing imagery, to enhance accuracy.

ML algorithms and deep learning models will analyze environmental variable features, such as humidity, temperature, soil texture, and precipitation, to estimate soil moisture content. This soil moisture prediction model will help farmers and agronomists optimize irrigation scheduling, prevent overwatering or drought stress, and improve the water resource management. The implementation of this technology will lead to sustainable agriculture, reduced water wastage, and improved crop yield, making precision farming more accessible and data-driven. This manuscript is presented as below: Section 2 indicates a literature review, and Section 3 describes discussion and future directions.

2. LITERATURE REVIEW

Soil moisture prediction is a crucial aspect of precision agriculture, as it influences irrigation scheduling and water resource management. Several studies have explored ML methods to increase soil moisture prediction accuracy. Traditional methods, such as gravimetric analysis and time-domain reflectometry (TDR), provide precise measurements but are limited in scalability and labour-intensive. Recent advancements integrate IoT-based sensors, meteorological inputs, and remote sensing data to improve accuracy. Various ML techniques, including Gradient Boosting, Support Vector Machines (SVM), Random Forest (RF), and Deep Learning techniques like LSTM and CNN, have been applied to model soil moisture dynamics. These techniques utilize historical data and real-time inputs to enhance the reliability of predictions. Existing research has demonstrated the effectiveness of hybrid models that combine multiple algorithms for improved accuracy. Future work suggests integrating edge computing for real-time analysis, enhancing model interpretability for practical use by farmers, and incorporating additional environmental parameters to refine predictions [5]. Several papers summarize the prediction of soil moisture using ML techniques. Summarization is presented in a table that contains the paper title, the used dataset, methods, tools, advantages, issues, and accuracy, as shown in Table 1.

TABLE I. SUMMARY OF PREVIOUS STUDIES

S. No.	Paper Reference	Data Set/ Features	Technique/ Algorithm used	Advantages	Issues/ Disadvantage	Accuracy
1.	[1]	Temperature, Moisture, pH, Conductivity, Nitrogen, Phosphorus, Potassium	Multiple Linear Regression (MLR)	1. Improved agricultural efficiency and productivity. 2. Cost effective 3. Data-driven decision making. 4. Scalability	1. Narrow focus on only Nitrogen, Phosphorus, Potassium. 2. Overfitting and accuracy issue. 3. Regional limitations in the applicability of the model.	78%
2.	[2]	Soil type, pH, Nutrient, Moisture, Soil texture, Soil depth, Temperature, Conductivity, Soil organic matter	Randon Forest (RF), SVM	1. Improved crop yields. 2. Efficient resource utilization. 3. Time and cost effective. 4. Improved decision making, scalability across regions and sustainability.	1. High initial setup cost 2. potential overfitting 3. Complexity of soil variations	89%
3.	[3]	Soil texture, Moisture, Soil nutrients, Soil organic matter	RF, SVM, ANN, Deep Learning	1. Enhance crop yield, scalability, and sustainability. 2. Real-time decision making. 3. Adaptability	1.False positive and errors	80-95%
4.	[4]	Soil depth, pH, Nitrogen, Potassium, Phosphorus, Water holding capacity, Porosity, Conductivity, Carbon	Decision tree, SVM, KNN	1. Improved crop yield 2. Cost effective 3. Scalability and Versatility	1. Limited accuracy 2. Technical complexity	80%
5.	[11]	629 images of 38 soil samples, direct and indirect sunlight conditions	ANN, CNN, MLP, LR, SVM, PLS, RF	1. Soil moisture prediction using smartphone will be quicker, 2. Less expensive, 3. Easier to assess. 4. It predicts accurate soil colour values and soil moisture values.	1. High content moisture was found in the dark-coloured soils. 2. Other factors like geology, topography, climate, and so on, were not considered explicitly.	99%
6	[6]	Wavelength Range-visible (400-700nm), near infrared (700-2500nm), Reflectance / Absorbance values, Nutrient Content, soil pH, Moisture Content.	Gradient Boosted Regression Tree, RF	1.AI techniques shows the possibility of predicting crop selection, soil fertility, based on factors such as, soil nutrients, soil pH and precipitation.	1. Noisy and incomplete Data. 2. Overfitting 3. High computational Costs 4. Senor limitations.	72%
7	[7]	Images of the soil.	Decision Tree (DT), Naïve Bayes (NB), and SVM image classifier.	1. Automated soil quality prediction without manual testing 2. High accuracy 3. Helps in crop yield prediction and decision-making.	1. NB, DT gave poor accuracy (70–80%) 2. WEKA, RapidMiner, and Orange were not suitable for the image dataset. 3. Azure ML was unable to display all soil properties.	96%
8	[8]	Portable X-ray fluorescence data and Vis-NIR (visible	RF, Partial least Squared regression (PLSR),	1. Quick and simple prediction of soil properties. 2. Maximum performance was attained using RDNet.	1. DL techniques are constrained by high-dimensional data and very small sample sizes. 2. Due to a lack of training	82-85%, RDNet: R^2 = 0.86

		and near-Infrared spectroscopy) data.	SVM, CNN (VGG, DenseNet), WaveNet, RDNet (Residual Dilated Neural Network).	3. Visualizations cut down errors and analysis time. 4. Scalable for soil samples that are dispersed throughout the world .	samples, CNN/DenseNet performed poorly.	
9	[9]	Soil moisture content, field slope, SOM, rainfall, temperature, pH, nitrogen, phosphorus, and potassium values.	Linear, Lasso, and polynomial regression K-NN, AdaBoost SVR, CNN, MLP, Gaussian NB	1. Detailed analysis of ML techniques for predicting crop yield. 2. The integration of several datasets is highlighted. 3. Determines precision agriculture's opportunities and gaps.	1 Data availability varies by region. 2. Issues with preprocessing and data quality. 3. Standardized benchmark datasets are lacking..	90-95%
10	[10]	MODIS data, Crop images, Moisture sensor data, thermal images	SVM, Linear Regression, AdaBoost, Multilayer Perceptron (MLP), Random Forest	This hybrid technique is efficient for smart farming.	Not much accurately predicted.	82%(RF) 82% (AdaBoot),73% (SVM),93.3 % (MLP)
11	[21]	Three datasets – Bragg's Farm, TAMU North American, OzNet Hydrological Monitoring Network with Daily average soil moisture and Soil temperature	SVR, MLR, RNN	1. Easy to understand and effective for short-term forecasting. 2. Less sensitive to outliers. 3. Dataset from different climate conditions	1. Accuracy decreases with a larger horizon (7-day). 2. Requires more data. 3. Prone to vanishing/exploding	1-day: MSE 0.15, R^2 0.96 2-day: MSE 0.40, R^2 0.90 7-day: MSE 1.2, R^2 0.713 (MLR)
12	[22]	29 weather stations with 32 features like water capacity, temperature, rainfall, wind	(CNN-LSTM Genetic Algorithm, SVM, RF, ANN, PhyI-DGA-CaDT Framework (Physics-Informed Dynamic Graph Attention Causal Decision Transformer)	1. Captures spatial & temporal patterns. 2. Robust under uncertainty. 3. Supports real-time decision making. 4. Good for small to medium datasets 5. Handles big IoT data efficiently 6. Easy to implement. 7. Improves resource allocation (water, fertilizer, energy)	1. High computational cost. 2. Requires a large labeled dataset 3. IoT sensors prone to noise & missing data	98%
13	[23]	Volumetric water content (VWC) at 10 and 30 cm depths, aggregated into hourly, daily, weekly, and monthly series	Multihead LSTM	1. Show long and short-term and dependencies in soil moisture time series. 2. Ensemble technique improves generalization compared to a single-head LSTM. 3. Provides forecasts for monthly, weekly, hourly, daily, and bases. 4. Outperforms individual LSTM techniques.	1. Less accuracy for monthly prediction due to the small training data size. 2. Performance is sensitive to hyperparameters.. 3. Lack of auxiliary inputs (temperature, precipitation, etc.). - Overfitting risk with small training data.	R^2 = 95.04% for soil moisture forecasting up to one month ahead
14	[24]	soil temperature at 5 cm, precipitation, soil moisture at 5 cm depth, atmospheric temperature, and time variables (year, day of year, hour)	Encoder Decoder LSTM with Residual Learning (EDT-LSTM)	1. Detects intermediate time-series dependencies. 2. Residual learning reduces deterioration for deep networks. 3. Encoder–decoder LSTM outperforms traditional LSTM. 4. Shows robustness for climates and vegetation	1. High computational requirements compared to simpler models. 2. Model performance depends mainly on hyperparameters like batch size, iterations, and time step.	Achieved R^2 = 0.966 (1-day), 0.941 (3-day), 0.915 (5-day), 0.881 (7-day), 0.879 (10-day)
15	[25]	ERA5 climate reanalysis data	Long Short-Term Memory (LSTM)	1. Captures temporal dependencies in soil	1. Sensitive to outliers at some stations.	LSTM with R^2 >

		(2011–2020) and Yr weather forecast (2019–2020), including daily max/min temperature, precipitation, vapour pressure deficit, and soil moisture from 28 meteorological stations in Serbia.	network (compared with ARIMA and Random Forest).	moisture dynamics. - Lower errors vs. ARIMA and RF. - Robust across soil types and altitudes. - Scalable using open-source data.	- Requires more computational resources. - Slight lag compared with sensor data.	0.90 and MAE ≈ 0.021

Researchers in [17]–[20] have conducted a comparative analysis of various ML, soft computing (SC), and data mining (DM) techniques used in diabetes and thunderstorm prediction. Their findings discuss the strengths, limitations, methodologies, tools employed, prior studies, and prospective advancements. The tools and techniques have also been evaluated based on criteria such as advantages, challenges, and applications.

3. DISCUSSION AND FUTURE DIRECTIONS

.

Predicting soil moisture remains a complex challenge. Several research studies have examined various datasets, methodologies, and tools, as well as their benefits and limitations. In this context, different SC, ML, and DM methods have been used to predict soil moisture. However, an effective method is needed for accurate lightning and thunderstorm prediction. Therefore, the authors summarize the future guidelines of several studies, along with current work, in the subsequent Table II.

TABLE II. FUTURE RESEARCH DIRECTIONS: A SUMMARY OF EXISTING WORK

S.No.	**Paper**	**Exiting Work**	**Future Work**
[1]	Eftychia Taktikou et al. [11]	The project utilizes remote sensing techniques, primarily employing MODIS satellite data, including NDVI, Land Surface Temperature (LST), Diurnal LST (DLST), Apparent Thermal Inertia (ATI), and Soil Moisture Saturation Index (SMSI), as well as in-situ diele ctric sensors. Soil moisture was predicted at various depths using linear regression models.	This project can achieve higher accuracy using deep learning models, multi-sensor data fusion (e.g., Sentinel, Landsat, SMAP, SAR), and integration with IoT soil sensors. These approaches can capture non-linear relationships, provide higher spatial–temporal resolution, and enable real-time soil moisture monitoring for smart irrigation and climate applications.
[2]	Oliviu Matei et al. [12]	This paper used a data mining technique to predict soil moisture levels. Data mining uses sensor data (temperature, humidity, soil characteristics) to estimate soil moisture levels.	Advanced ML algorithms (e.g., Neural Networks, Random Forest, LSTM for time series) can be utilized for further improvement. Integration with IoT and satellite remote sensing will improve prediction accuracy and applicability in smart agriculture.
[3]	Mohamed Elsaadani et al. [13]	It associates CNNs (for take out spatial characteristics) and LSTMs (for capturing temporal dependencies) in a Convolutional LSTM (ConvLSTM) model. ConvLSTM is trained against reference soil moisture datasets, atmospheric variables, rainfall, and land cover information.	Hybrid ML models can be utilized to enhance accuracy. Integration with multi-source data, such as SMAP, Sentinel-1 SAR, or high-resolution optical data to improve spatial coverage and depth sensitivity.
[4]	Yanling Wang et al. [14]	This paper compared deep learning models (LSTM, CNN, Transformer, hybrids, attention-based, and GAN-LSTM) and machine learning models (RF, SVR, and ELM) for predicting soil moisture. The results indicated that LSTM was the most successful, while CNN–LSTM hybrids added complexity with little advantage, while FA-LSTM and GAN-LSTM provided additional enhancements. By employing t-SNE and SHAP analysis, the model's	Future work can focus on automating GAN-LSTM hyperparameter tuning and integrating physical hydrological principles with data-driven models to enhance long-term prediction.

		interpretability improved.	
[5]	Mehmet Furkan Celik et al. [15]	The study utilized soil texture, topography, climate, and satellite data to develop an LSTM-based framework for short-term soil moisture prediction.	Future studies will combine LSTM with attention processes to better capture temporal interdependence and feature relevance. This goals to increases the interpretability of the model's physical relevance, as well as its forecast accuracy.
[6]	Yeguang li et al. [16]	The paper presents an adaptive weight LSTM (AW-LSTM) multi-task learning technique that improves global soil moisture prediction by dynamically allocating weights between tasks based on correlation and gradient behaviour. Existing work combines soil moisture with related variables (e.g., soil temperature, heat flux) and shows that adaptive weighting outperforms both single-task and fixed-weight models.	For the model's future development and expansion to higher-resolution data, testing performance in various climates and geographical areas, combining process-based and data-driven methodologies, and enhancing interpretability to better match predictions with physical laws.

The authors recommend that future research efforts focus on designing an expert system for soil moisture prediction to enhance the accuracy of predictions.

REFERENCES

1. Madhumathi, R., Arumuganathan, T., Lyer, R. S., Shruthi, R., & Shruthhi, K. (2020). Soil nutrient analysis using machine learning techniques. National E-Conference on Communication, Computation, Control and Automation (CCCA-2020).
2. Reddy, L. V., Ganesh, D., Kumar, M. S., Gogula, S., Rekha, M., & Sehgal, A. (2024). Applying machine learning to soil analysis for accurate farming. MATEC Web of Conferences, 392, 01124. https://doi.org/10.1051/matecconf/202439201124
3. Awais, M., Naqvi, S. M. Z. A., Zhang, H., Li, L., Zhang, W., Awwad, F. A., Ismail, E. A. A., Khan, M. I., Raghavan, V., & Hu, J. (2023). AI and machine learning for soil analysis: An assessment of sustainable agricultural practices. Bioresources and Bioprocessing, 10(90), 1–16. https://doi.org/10.1186/s40643-023-00710-y
4. Kanade, P. (2023). Soil analysis using machine learning. British Journal of Multidisciplinary and Advanced Studies: Earth Sciences, 4(6), 1–11. https://doi.org/10.37745/bjmas.2022.0350
5. Hossain, M. R. H., & Kabir, M. A. (2023). Machine learning techniques for estimating soil moisture from smart phone captured images. Agriculture, 13(3), 574. https://doi.org/10.3390/agriculture13030574
6. Divya, A., Josphineleela, R., & Sheela, L. J. (2024). A machine learning-based approach for prediction and interpretation of soil properties from soil spectral data. Journal of Environmental Biology, 45(1), 96–105.
7. Ramya, R., Ranjitha, D., Revathy, T., Vijeth, P. R., & Ranjitha, U. N. (2019). Prediction of soil quality using machine learning approach. International Journal of Computer Science and Engineering, 7(14), 279–283.
8. Pham, V., Weindorf, D. C., & Dang, T. (2021). Soil profile analysis using interactive visualizations, machine learning, and deep learning. Computers and Electronics in Agriculture, 191, 106539.
9. Huang, Y., Srivastava, R., Ngo, C., Gao, J., Wu, J., & Chiao, S. (2023). Data-driven soil analysis and evaluation for smart farming using machine learning approaches. Agriculture, 13(9), 1–22.
10. Madhumitha, M., & Ambikapathy, R. (2024). Soil analysis and crop recommendation using deep learning. International Research Journal of Modernization in Engineering, Technology and Science, 6(8), 1–5.
11. Taktikou, E., Bourazanis, G., Papaioannou, G., & Kerkides, P. (2016). Prediction of soil moisture from remote sensing data. In Proceedings of the 2nd International Conference on Efficient & Sustainable Water Systems Management toward Worth Living Development (EWaS2). Procedia Engineering, 162, 309–316. https://doi.org/10.1016/j.proeng.2016.11.066
12. Matei, O., Rusu, T., Petrovan, A., & Mihut, G. (2017). A data mining system for real time soil moisture prediction. In Proceedings of the International Conference Inter disciplinary in Engineering (INTER-ENG 2016). Procedia Engineering, 181, 837–844. https://doi.org/10.1016/j.proeng.2017.02.475
13. ElSaadani, M., Habib, E., Abdelhameed, A. M., & Bayoumi, M. (2021). Assessment of a spatiotemporal deep learning approach for soil moisture prediction and filling the gaps in between soil moisture observations. Frontiers in Artificial Intelligence, 4, Article 636234. https://doi.org/10.3389/frai.2021.636234
14. Wang, Y., Shi, L., Hu, Y., Hu, X., Song, W., & Wang, L. (2024). A comprehensive study of deep learning for soil moisture prediction. Hydrology and Earth System Sciences, 28, 917–943. https://doi.org/10.5194/hess-28-917-2024
15. Celik, M. F., Isik, M. S., Yuzugullu, O., Fajraoui, N., & Erten, E. (2022). Soil moisture prediction from remote sensing images coupled with climate, soil texture and topography via deep learning. Remote Sensing, 14, 5584. https://doi.org/10.3390/rs14215584
16. Li, Y., Liu, H., & Lv, T. (2025). A multi-task learning model for global soil moisture prediction based on adaptive weight allocation. Scientific Reports, 15, 18631. https://doi.org/10.1038/s41598-025-01894-3
17. Choubey, D. K., & Paul, S. (2016). Classification techniques for diagnosis of diabetes disease: A review. International Journal of Biomedical Engineering and Technology, 21(1), 15–39.
18. Choubey, D. K., Paul, S., & Bhattacharjee, J. (2014). Soft computing approaches for diabetes disease diagnosis: A survey. International Journal of Applied Engineering Research, 9, 11715–11726.
19. Bala, K., Choubey, D. K., & Paul, S. (2017). Soft computing and data mining techniques for thunderstorms and lightning prediction: A survey. In Proceedings of the International Conference on Electronics, Communication and Aerospace Technology (ICECA) (pp. 42–46). Coimbatore, India.
20. Bala, K., Choubey, D. K., Paul, S., & Lala, M. G. N. (2018). Classification techniques for thunderstorms and lightning prediction: A survey. In Soft-Computing-Based Nonlinear Control Systems Design (pp. 1–24). IGI Global. https://doi.org/10.4018/978-1-5225-3531-7.ch001
21. Prakash, S., Sharma, A., & Sahu, S. S. (2018). Soil moisture prediction using machine learning. In Proceedings of the 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT) (pp. 1–6). IEEE. https://doi.org/10.1109/ICICCT.2018.8473260
22. Zhang, M., Al-Fuqaha, A. S., & Hossain, M. A. (2025). Improving soil moisture prediction using Gaussian process regression. Internet of Things and Cyber-Physical Systems, 5, 175–188. https://doi.org/10.1016/j.iotcps.2025.03.004
23. Datta, P., & Faroughi, S. A. (2023). A multihead LSTM technique for prognostic prediction of soil moisture. Geoderma, 433, 116452. https://doi.org/10.1016/j.geoderma.2023.116452.
24. Q. Li, Li, Z., Shangguan, W., Wang, X., Li, L., & Yu, F. (2022). Improving soil moisture prediction using a novel encoder–decoder model with residual learning. Computers and Electronics in Agriculture, 195, 106816. https://doi.org/10.1016/j.compag.2022.106816
25. Filipović, N., Brdar, S., Mimić, G., Marko, O., & Crnojević, V. (2022). Regional soil moisture prediction system based on long short-term

memory network. Biosystems Engineering, 213, 30–38. https://doi.org/10.1016/j.biosystemseng.2021.11.019

AUTHORS:

Kanchan Bala received her B.E. degree in Computer Science & Engineering from Rajasthan University, India, and her M.Tech degree in Computer Science from Banasthali University, Rajasthan, India. She received PhD at the Department of Computer Science, Birla Institute of Technology Mesra, Ranchi, Jharkhand, India. She was a Project Assistant with the IC Design Department, CEERI-CSIR, Pilani, Rajasthan. She is currently an Assistant Professor with DSTTE, Government College, Bihar. India. Her areas of interest include Machine Learning, Artificial Intelligence, Image Processing, Internet of Things, and microwave tubes.

Corresponding Author E-mail: Kanchanbala237@gmail.com

Modal Kumari completed her BTech degree in Computer Science & Engineering from B.E.U. Patna, India in 2025. Her interest areas are Artificial Intelligence, Machine Learning, Internet of Things (IoT), Data Science, Operating Systems and Embedded Systems. E-mail: modalkumari513@gmail.com

Gajala Praveen received her B.Tech degree in Computer Science & Engineering from Bhagalpur Bihar, Gaya, India. She is currently an assistant professor at Gaya College of Engineering, Gaya, with DSTTE, Bihar, India. Her research interests include blockchain technology, natural language processing, cloud computing, and distributed computing. She has published research papers in journals, conference proceedings, and book chapters.

E-mail: praweengajala@gmail.com

Anju Kumari completed her BTech degree in Computer Science & Engineering from B.E.U. Patna, India in 2025. Her interest areas are Artificial Intelligence, Machine Learning, App and Web Development.

E-mail: anjuukumari001@gmail.com

Anamika Kumari completed her BE degree in Computer Science & Engineering from B.E.U. Patna, India in 2025. Her interest areas are Data Science, Software Engineering, Embessed Systems, Operating Systems and Machine Learning.

E-mail: priyakri293@gmail.com