Load Forecasting with Cat Boost in Cloud Environment for Enhanced Energy Management Efficiency

S Murugan
Department of Biomedical Engineering, Saveetha School of Engineering,
Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai,
Tamil Nadu, India

Dr. Balakumar Vijayaraman
Sub Divisional Engineer (Security), MPLS Network Operations
Centre, BSNL, Bengaluru, India,

Abstract
Accurate load forecasting helps optimize energy management systems by estimating energy demand. CatBoost, a sophisticated gradient boosting algorithm, is used in clouds to improve energy management load predictions. This strategy uses CatBoost's enhanced skills in processing massive datasets and modeling complicated connections in time-series to improve energy demand projections. Energy suppliers should reduce costs, ensure system stability, and make smart resource allocation choices. Scalable and accessible cloud deployment allows real-time data processing and interaction with energy management systems. This technology might change energy forecasting by improving accuracy and reliability, allowing better energy management solutions for sustainable development. Taken from Load_Data_Metrics 5 areas and 5 parameters are sampled. Average Load (MW): 70.64-103.62, Peak Load (MW): 159.39-277.06, Off-Peak Load (MW): 60.15-93.16, Variance (MWÂ²): 265.22-388.57, Min Load (MW): 13.95-35.84. Forecast_Accuracy data. Five test scenarios with five parameters are sampled. Results: RMSE (MW): 3.09-9.65, MAE (MW): 1.68-4.89, MAPE (%): 2.29-13.2, RÂ² Score: 0.867-0.986, Training Time (s): 17.96-40.9. Alert_Trends samples 5 areas and 5 parameters. Alerts Generated: 23–44, Severity (1–10): 1–6, Average Resolution Time (min): 8.01–20.88 Morning, afternoon, evening, and night are peak alert times.

Keywords
Cat Boost, Load Forecasting, Energy Management, Cloud Computing, Forecasting Accuracy

1. Introduction

Machine learning has improved energy demand prediction in energy management systems, improving operational efficiency. Energy management relies on load forecasting to estimate energy consumption over time. Accurate forecasting optimizes resource allocation, energy use, and operating costs. Due to its excellent prediction accuracy and capacity to handle categorical variables, CatBoost, a gradient boosting method for structured data, provides reliable load forecasting solutions. CatBoost's scalability and real-time processing improve on the cloud, making it suited for dynamic energy management systems. This project aims to use CatBoost on the cloud for accurate load forecasting. A scalable and efficient platform for massive datasets and energy management insights is the goal. Advanced forecasting helps energy suppliers predict demand, reduce waste, and assure system stability. CatBoost is appropriate for energy load forecasting since it can handle categorical information without preprocessing and is computationally cheap. With cloud platforms' processing capability, it permits real-time analysis and large-scale data management. Cloud integration lets energy companies use forecasting models remotely, collaborate, and distribute upgrades without downtime. These characteristics enable proactive energy distribution and control, decreasing supply-demand mismatches and guaranteeing system stability.

Section 2 covers classic load forecasting systems' data scalability, categorical variable management, and real-time processing issues. This section covers how machine learning algorithms and cloud computing solve these problems, highlighting the necessity for

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innovation. Section 3 describes the framework's design, combining CatBoost with cloud platforms to improve forecasting. Data preprocessing, feature engineering, model training pipelines, and the cloud's role in scalability and fault-tolerant processing are covered.
Section 4 uses case studies and performance measurements to assess the framework's efficacy. To prove system dependability, MAPE, computational efficiency, and scalability are examined. Real-world smart grid and renewable energy use cases demonstrate practical applications. Section 5 closes with a review of CatBoost's cloud load forecasting advantages and prospects for improvement. For hybrid forecasting systems, real-time data streaming, model interpretability, and other machine learning methods are being included.

2. Literature Survey

Feature Importance-Based Multi-Layer CatBoost Model for Student Performance Prediction. This study offers a feature importance-based CatBoost model to improve student performance prediction. CatBoost's multi-layer architectures and feature selection isolate academic success factors to improve prediction accuracy. Comparing CatBoost to standard models shows its effectiveness in managing academic data's non-linear correlations. Educational stakeholders wanting data-driven insights into student achievement may use this model to improve interventions and resource allocation to optimise educational outcomes [1]. CatBoost-based hybrid models predict student academic performance. A CatBoost-based hybrid machine learning model evaluates student performance. Educational analytics with substantial student data variance benefits from this approach's sophisticated pattern identification. The model might be used in adaptive learning and targeted academic help to anticipate performance [2]. Threat detection accuracy comparison: LightGBM vs. CatBoost. This study compares CatBoost with LightGBM for threat detection. While both models are competent, CatBoost outperforms both in recognising complex threat patterns, promising applications where accuracy and dependability are crucial for proactive threat mitigation [3]. Ensemble CatBoost Vehicle Classification on Complex Datasets. A complicated dataset of car attributes shows the ensemble CatBoost model's vehicle classification performance. CatBoost's high-dimensional data processing accuracy helps the model identify vehicle kinds. The ensemble technique improves resilience, making it useful for transport infrastructure management [4].
Predicting Rainfall using CatBoost and Random Forest. This study compares rainfall prediction methods CatBoost and Random Forest. The concept is useful in agricultural and disaster management, because precise weather predictions support preventative interventions [5]. CatBoost-Based Feline Infectious Peritonitis Diagnosis. The study employs CatBoost to automate FIP diagnosis. The approach might improve automated diagnostics by providing a scalable solution for medical applications that need precise illness prediction [6]. CatBoost Predicts Weekly Subtropical and Sub-Humid Pan Evaporation. Hydrological investigations benefit from this model's non-linear variable interactions to properly anticipate evaporation. Its great accuracy makes it useful for resource management in agriculture, where water utilisation is crucial, and forecast water needs directly affect efficiency [7]. Health Tracker LightGBM, CatBoost, Explainable Boost Classifier. A health monitoring system uses CatBoost with other classifiers to accurately forecast health using CatBoost's categorical data processing. Integration helps health workers understand patient circumstances and customise therapies, suggesting broad remote patient monitoring [8]. Financial Risk Prediction for Listed Companies Using CatBoost-Based Ensemble Learning. Its flexibility to high-dimensional financial data makes CatBoost a powerful prediction tool that meets risk management professionals' changing demands, allowing better informed financial decision-making in unpredictable markets [9]. CatBoost predicts Google Play Store app ratings. The algorithm uses CatBoost to estimate Google Play Store app ratings using user comments and usage information. This application shows CatBoost's flexibility in analysing customer-driven data, providing developers with practical insights to improve user experience and app engagement [10]. SHAP Explainability with CatBoost, XGBoost, and LightGBM Predicts Total Dissolved Gas. SHAP study predicts total dissolved gas levels utilising CatBoost, XGBoost, and LightGBM to address machine learning explainability. By explaining prediction model outputs in ecological monitoring, this technique improves

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environmental management and regulatory compliance [11]. Gastric Cancer Detection in Histopathology Image Analysis using Hybrid Deep Learning and CatBoost. This study uses deep learning and CatBoost to identify stomach cancer in histopathology images. The algorithm might help physicians make accurate diagnostic predictions in medical image analysis [12].
High-Accuracy Obesity Prediction using CatBoost Machine Learning Model. This approach helps policymakers and practitioners identify at-risk people and develop targeted obesity-related health treatments in proactive public health programs [13]. Power System Transient Stability Assessment using GHM-Enhanced CatBoost. This approach can solve energy infrastructure management problems including predictive maintenance and real-time stability monitoring [14]. Correct Customer Churn Prediction Using CatBoost for Data-Driven Decisions. In high-turnover industries like telecommunications and banking, client retention techniques are crucial to competitive advantage [15]. Smart Agriculture's Physical Layer Intrusion Detection using CatBoost. This application highlights the model's relevance in growing domains that need strong cyber security, such as agriculture and IoT-driven enterprises [16].
CatBoost CFST Column Load-Bearing Capacity Prediction. Centrally compressed, short CFST columns with circular cross-sections are tested for load-bearing capability using CatBoost. The model's versatility to structural design makes it useful in civil engineering, where load-bearing predictions are crucial for structural integrity [17]. CatBoost, XGBoost, and LightGBM Algorithms Detect Early-Stage Diabetes Risk. This study compares CatBoost, XGBoost, and LightGBM for early-stage diabetes risk detection. This comparison shows CatBoost's benefits in healthcare, as early illness prediction improves preventative health outcomes [18]. CatBoost Classifier predicts online shoppers' purchase intentions. Digital retail benefits from the model's category feature processing, which predicts customer purchasing patterns and personalises shopping experiences [19]. Compacted Bentonite Hydraulic Conductivity Modelling using Constrained CatBoost and Bootstrap. This study predicts unsaturated hydraulic conductivity in compacted bentonite using restricted CatBoost and bootstrap analysis. CatBoost processes environmental data to accurately simulate hydraulic conductivity, a crucial geotechnical engineering element. Environmental and civil engineering, notably waste containment and water retention systems, need bentonite knowledge for safe and effective design [20].

3. Proposed Methodology

The solution combines sophisticated load forecasting methodologies with the functionalities of CatBoost, an effective gradient boosting library, inside a cloud infrastructure. This integration aids energy suppliers in attaining optimum resource distribution and cost minimization while accommodating variable energy requirements. Figure 1 shows a schematic of the steps used to gather and prepare data for load forecasting. A cloud preprocessing system receives raw data from energy meters, weather systems, and use records. Before being transformed into a structured format, the raw data is cleaned to eliminate mistakes, normalised to guarantee consistency, and processed. A central repository stores the processed data, making it ready to be used in CatBoost models. Accurate load forecasting relies on the architecture's dependable and scalable processing of real-time data. Better forecasting models and useful insights for energy management are made possible by the smooth integration of various data sources.

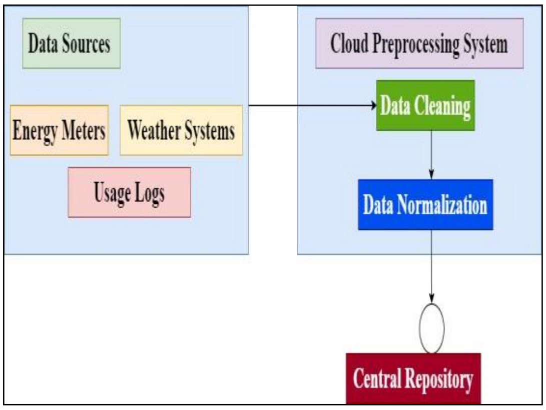

Figure.1. Block Diagram of Data Collection and Preprocessing Architecture

A. Data Acquisition and Preprocessing

The system collects energy usage data from diverse sources, such as smart grids, residential meters, and industrial sensors. Supplementary inputs, including meteorological trends, seasonal fluctuations, and historical use data,

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are included to provide a complete dataset. The process flow for training and deploying CatBoost models is shown in this figure from Figure 2. Model training takes pre-processed data as input and makes use of factors including user profiles, weather data, and historical loads. After training is complete, the model is optimised and validated to make sure it's accurate. After optimisation, the model is put into action in a cloud inference system to provide predictions in real-time.

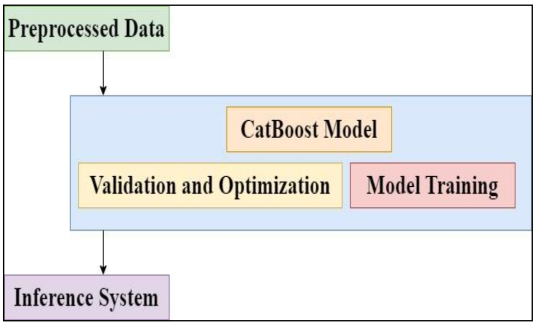

Figure.2. Block Diagram of CatBoost Training and Model Deployment Architecture

B. Feature Engineering and Selection

Feature engineering analyzes essential variables affecting energy consumption, including temperature, humidity, time of day, and user activity patterns. The development of significant features enhances the model's predicted accuracy. Automated machine learning (AutoML) methodologies augment feature engineering, allowing the system to adjust to novel datasets and evolving energy consumption patterns over time. This schematic from Figure 3 shows the method for visualizing and alerting. Visual dashboards that showcase indicators such as load trends, peak demand times, and use patterns are presented on top of the predictions made by CatBoost models.

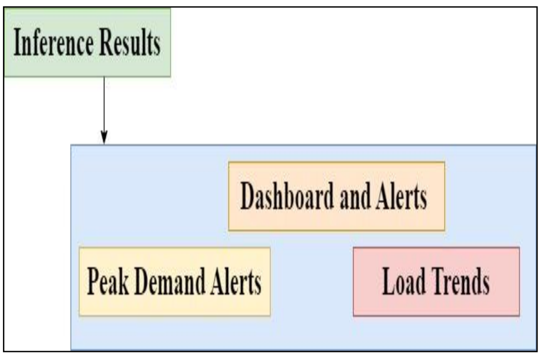

Figure.3. Block Diagram of Forecast Visualization and Alert System

C. Model Development and Enhancement

CatBoost is used for its exceptional management of categorical data and its capacity to achieve high accuracy with less human adjustment. Model checkpoints and versioning provide transparency and repeatability of the training process. Figure 4 shows the whole process flow for load forecasting. A preprocessing system ingests data from energy meters, weather systems, and use records and cleans and normalizes it. For both training and real-time prediction, CatBoost models are given the structured data.

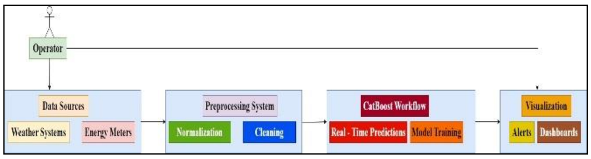

Figure.4. Data Flow Diagram of Load Forecasting Workflow

D. Instantaneous Prognostication

The CatBoost model, once trained, is put on a cloud platform, enabling real-time energy demand forecasting. These forecasts are customized to meet the requirements of many stakeholders, including grid operators, utility providers, and regulators. Integration with cloud-based APIs facilitates uninterrupted connection between the forecasting module and other systems. Figure 5 provides a high-level picture of the load forecasting system. A preprocessing system is used to gather data from many sources, including weather systems, logs, and Internet of Things (IoT) devices. Then, CatBoost models are used for analysis. Engineers are notified of possible dangerous circumstances via alerts, and predictions are shown on dashboards.

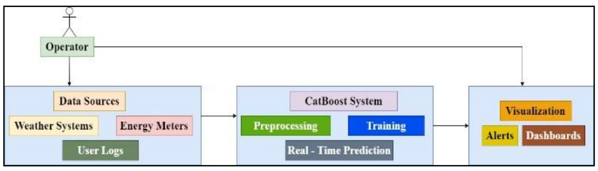

Figure.5. Overview Diagram of CatBoost Load Forecasting Ecosystem

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E. Data Visualization and Reporting

Technology offers an accessible interface for viewing predicted outcomes and monitoring energy use trends. Users may use heatmaps, time-series plots, and prediction trendlines to provide actionable information. Customizable views enable stakeholders to concentrate on certain geographic areas, temporal spans, or energy sectors. Automated reporting functionalities encapsulate essential insights and provide comprehensive reports in accessible forms, including PDFs and spreadsheets. These reports may be disseminated to decision-makers, guaranteeing informed plans for energy management. The visualization tools are designed for accessibility, rendering intricate data understandable to both technical and non-technical users.

F. Scalability and Flexibility

The system is designed for scalability, supporting a growing array of data sources and raising data volumes. Cloud architecture facilitates the smooth integration of novel information, including developing renewable energy sources and supplementary IoT devices. This adaptability guarantees the system's continued relevance as the energy industry progresses. Adaptability is a crucial characteristic, since the system use transfer learning to modify the CatBoost model for other areas, sectors, or operating situations. This ability guarantees uniform forecasting precision across many circumstances. Containerization solutions like Docker provide seamless deployment and migration across various cloud environments.

4. Results and Discussion

A. Safety and Adherence

Security is emphasized to safeguard critical energy consumption data from unwanted access and breaches. The system utilizes sophisticated encryption methods, secure communication protocols, and role-based access managementThe inherent security capabilities of cloud providers, such intrusion detection and threat monitoring, enhance the entire security architecture. Figure 6 displays important indicators derived from data on energy load for five different locations. Average, peak, off-peak, variation, and minimum loads are all metrics to consider. As an example, Region A exhibits a very variable demand profile, with a peak load of 210 MW and an average load of 75 MW. With the use of these measures, we can examine trends in energy use and make more precise projections about future demand. Engineers can improve grid efficiency, cut down on waste, and maximise energy output by studying load distributions.

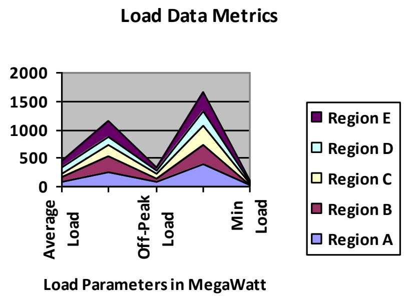

Figure.6. Load Data Metrics

Table 1 of CatBoost's advanced features positions it as a formidable candidate for load forecasting in a cloud setting. Its capacity to effectively handle categorical data reduces preprocessing requirements, while scalability guarantees the management of large datasets. Gradient boosting enhances predictive accuracy, essential for forecasting energy load peaks.

Table.1 Key Features of Catboost for Load Forecasting in Cloud Environment

Feature	Description	Function	Benefit	Example Use Case
Gradient Boosting	Employs gradient boosting on decision trees	Enhances predictive accuracy	Reduces forecast errors	Predicting energy load peaks
Handling Categorical Data	Processes categorical variables effectively	Simplifies data preprocessing	Improves model efficiency	Consumer usage classification
Scalability	Adapts to large datasets	Supports cloud-based operations	Enables large-scale forecasting	Utility load forecasting
Speed Optimization	Ensures faster training and prediction	Reduces computational costs	Speeds up deployment	Real-time forecasting
Cloud Integration	Seamlessly integrates with cloud platforms	Enables remote accessibility	Improves collaboration	Energy provider monitoring

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B. Economic Efficiency and Energy Conservation

The technology enhances cost efficiency via the optimization of energy management procedures and the reduction of operational overheads. Precise load forecasting reduces dependence on costly peak power production and facilitates the incorporation of renewable energy sources. The cloud-based design of the system guarantees cost-effectiveness and accessibility, providing sophisticated forecasting solutions to enterprises of varying sizes. Figure 7 displays the results of the evaluation of the CatBoost models' performance in load forecasting. The metrics that are included in the analysis are R^2 scores, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Scenario 3 shows a very accurate forecast with a 4.5 MW RMSE and a R^2 score of 0.94. The model's computational efficiency is shown by the training time metric.

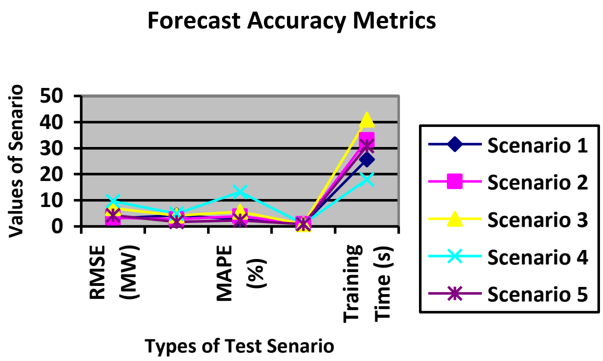

Figure.7. Forecast Accuracy Metrics

Table 2 of CatBoost demonstrates superior accuracy and efficient training, crucial for precise energy load forecasting. Its automated management of category and missing data streamlines preparation, save time and effort. Versatility facilitates its use in many energy management contexts, while cloud compatibility guarantees scalability and remote access.

Table 2. Advantages of using Catboost for Energy Load Forecasting

Advantage	Description	Function	Benefit	Challenge
High Accuracy	Provides precise predictions	Reduces forecasting errors	Improve decision-making	Requires quality data input
Automatic Handling	Manages categorical and missing data	Simplifies data processing	Reduces time and effort	May need parameter tuning
Efficient Training	Optimized for faster model training	Handles large datasets	Reduces computational time	High memory requirements
Versatility	Adapts to various load forecasting tasks	Supports diverse use cases	Broadens application scope	Learning curve for users
Cloud Compatibility	Supports deployment in cloud environments	Enhances scalability	Enables remote forecasting	Dependent on cloud infrastructure

C. Impact on Society and the Environment

CatBoost-based load forecasting enhances public welfare by guaranteeing a dependable electricity supply and mitigating disruptions. Augmented grid stability bolsters essential infrastructure, including healthcare and transportation, therefore enhancing community quality of life. The system promotes the shift to cleaner energy sources, reducing greenhouse gas emissions and advancing global sustainability objectives. The incorporation of renewable energy sources into the forecasting model enhances the usage of solar, wind, and hydroelectric electricity. The system optimizes resource use by precisely forecasting demand, hence reducing dependence on fossil fuels. This convergence with environmental principles

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makes the system an essential instrument for attaining a more sustainable and eco-friendly energy future. Figure 8 provides a consolidated view of the forecasting system's warning data for five different locations. The quantity of warnings, severity ratings, average resolution times, and peak alert durations are all considered metrics. Region B, for example, had 44 alarms, the majority of which occurred in the afternoon, and their average resolution time was 21 minutes. Seeing these patterns allows you to zero in on persistent problems and maximise your resources for fixing the most pressing concerns.

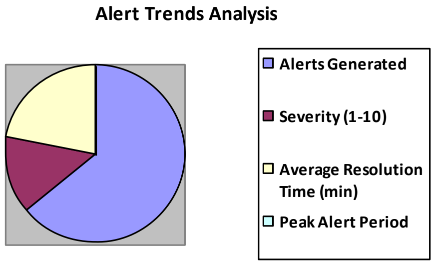

Figure.8. Alert Trends Analysis

D. Incorporation of IoT and Smart Grid Technologies

The suggested system utilizes IoT devices and smart grid technology to provide a more dynamic and real-time method for energy demand forecasting. Smart meters and IoT sensors provide detailed data on energy use, environmental factors, and infrastructural efficacy. These sensors transfer data directly to the cloud platform, facilitating real-time analysis and integration with the CatBoost model. Technology improves load distribution and problem detection in energy networks by collaborating with smart grid technologies. The system's predictive analytics guarantee optimal allocation of energy resources, alleviating pressure during high demand times. The uninterrupted transfer of data between IoT devices and the forecasting platform enables the system to function as an integrated entity, providing actionable insights with little delay.

5. Conclusion

CatBoost improves load forecasting accuracy, but its complexity and processing needs restrict it. CatBoost model training on big datasets is time- and cost-intensive. It might be challenging to integrate the model into cloud settings with current energy management systems. Accurate load forecasting may enhance energy management efficiency, resource allocation, cost, and grid stability. Volatile energy use habits and external variables like weather might impair prediction accuracy. To increase forecasting accuracy in varied operating situations, future aims include strengthening model resilience to such variables, cloud-based system scalability, and real-time feedback for ongoing model development. Taken from Load_Data_Metrics 5 areas and 5 parameters are sampled. Average Load (MW): 70.64-103.62, Peak Load (MW): 159.39-277.06, Off-Peak Load (MW): 60.15-93.16, Variance (MWÂ²): 265.22-388.57, Min Load (MW): 13.95-35.84. Forecast_Accuracy data. Five test scenarios with five parameters are sampled. Results: RMSE (MW): 3.09-9.65, MAE (MW): 1.68-4.89, MAPE (%): 2.29-13.2, RÂ² Score: 0.867-0.986, Training Time (s): 17.96-40.9. Alert_Trends samples 5 areas and 5 parameters. The alerts generated are 23–44, the severity (1–10) is 1–6, the average resolution time (min) is 8.01–20.88, and the peak alert period is morning, afternoon, evening, and night.

References

1. Z. Fan, J. Gou and S. Weng, “A Feature Importance-Based Multi-Layer CatBoost for Student Performance Prediction,” IEEE Transactions on Knowledge and Data Engineering, vol. 36, no. 11, pp. 5495-5507, 2024.

DOI: https://doi.org/10.5281/zenodo.19315871

2. S. R. Thumala, H. Madathala and V. M. Mane, "Azure Versus AWS: A Deep Dive into Cloud Innovation and Strategy," International Conference on Electronics and Renewable Systems (ICEARS), pp. 1047-1054, 2025.
3. V. Ramesh, “Evaluating Apache Kafka performance and operational efficiency: A comparative study of ZooKeeper and KRaft architectures,” International Journal of Computer Applications, vol. 187, no. 46, pp. 12–18, 2025.
4. P. RK, K. M. AboRas, and A. Youssef, “Application of an Ensemble CatBoost Model Over Complex Dataset for Vehicle Classification,” PLOS ONE, vol. 19, no. 6, pp. 1-26, 2024.
5. S. C. Hsu, A. K. Sharma, R. Tanone and Y. T. Ye, “Predicting Rainfall Using Random Forest and CatBoost Models,” in Proceedings of the 9th World Congress on Civil, Structural, and Environmental Engineering, pp. 1-8, 2024.
6. P. H. Kuo, Y. H. Li and H. T. Yau, “Development of Feline Infectious Peritonitis Diagnosis System by Using CatBoost Algorithm,” Computational Biology and Chemistry, vol. 113, pp. 1-21, 2024.
7. H. Madathala, S. R. Thumala, and G. Yeturi, “Optimizing cloud migration: Designing robust architectures for seamless transition from on-premises to Azure for SAP and database systems,” International Journal of Engineering Technology Research & Management, vol. 9, no. 1, 2025.
8. P. Pothupogu, Y. Santhakumar, A. Yenmanagandla, and A. Sriram, “Health Monitoring System Based on LightGBM, CatBoost and Explainable Boost Classifier,” 2nd World Conference on Communication and Computing, pp. 1-7, 2024.
9. H. Lu and X. Hu, “Enhancing Financial Risk Prediction for Listed Companies: A CatBoost-Based Ensemble Learning Approach,” Journal of the Knowledge Economy, vol. 15, no. 2, pp. 9824-9840, 2024.
10. S. R. Thumala, V. Mane, T. Patil, P. Tambe and C. Inamdar, "Full Stack Video Conferencing App using TypeScript and NextJS," 3rd International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS), pp. 1285-1291, 2025.
11. N. Ganesh, A. Sriram, S. N. Krishnan, and T. S. Rao, “Simultaneous enhancement and detection of brain tumors using GAN,” in Intelligent Computing—Proceedings of the Computing Conference. Cham, Switzerland: Springer Nature Switzerland, pp. 206–220, 2025.
12. D. Khayatian, A. Maleki, H. Nasiri, and M. Dorrigiv, “Histopathology Image Analysis for Gastric Cancer Detection: A Hybrid Deep Learning and CatBoost Approach,” Multimedia Tools and Applications, pp. 1-27, 2024.
13. A. Maulana, R. P. Afidh, N. B. Maulydia, G. M. Idroes and S. Rahimah, “Predicting Obesity Levels with High Accuracy: Insights from a CatBoost Machine Learning Model,” Infolitika Journal of Data Science, vol. 2, no. 1, pp. 17-27, 2024.
14. Z. Wang, “Data-Driven Transient Stability Assessment of Power Systems with a Novel GHM-Enhanced CatBoost Algorithm,” arXiv preprint arXiv:2410.19876, pp. 1-10, 2024.
15. S. R. Thumala, “Importance of business continuity and disaster recovery (BCDR) methodologies for organizations: A comparison study between AWS and Azure,” International Journal of Science and Research (IJSR), vol. 11, no. 12, pp. 1406–1415, 2022.
16. Z. Wei, F. Ning, K. Jiang, Y. Wang, Z. Bi, Q. Duan, J. Zhang and R. Li, “CatBoost-Based Intrusion Detection Method for the Physical Layer of Smart Agriculture,” in ITM Web of Conferences, vol. 60, pp. 1-8, 2024.
17. T. Kondratieva, A. Chepurnenko, K. Poliakova and K. Rodionov, “CatBoost Algorithms to Predict the Load-Bearing Capacity of Centrally Compressed Short CFST Columns of Circular Cross-Section,” in E3S Web of Conferences, vol. 583, pp. 1-7, 2024.
18. H. Madathala, S. R. Thumala, B. Barmavat, and K. K. S. Prakash, “Functional consideration in cloud migration,” International Peer Reviewed/Refereed Multidisciplinary Journal (EIPRMJ), vol. 13, no. 2, 2024.
19. V. Ramesh, “Performance benefits of reactive frameworks,” International Journal of Computer Applications, vol. 975, pp. 8887, 2025.

DOI: https://doi.org/10.5281/zenodo.19315871

20. R. Taherdangkoo, T. Nagel, C. Chen, M. Mollaali, M. Ghasabeh, O. Cuisinier, A. Abdallah and C. Butscher, "Modeling Unsaturated Hydraulic Conductivity of Compacted Bentonite Using a Constrained CatBoost with Bootstrap Analysis," Applied Clay Science, vol. 260, pp. 1-11, 2024.

DOI: https://doi.org/10.5281/zenodo.19315871