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An IoT-Enabled Framework for Real-Time Monitoring and Prediction of Methane Emissions in Sustainable Ruminant Farming

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Abstract: ***This paper presents the development of an Artificial Intelligence (AI) enabled Internet of Things (IoT) framework for methane emission monitoring and prediction in sustainable ruminant farming. Methane emissions from ruminant livestock are a significant contributor to greenhouse gas emissions and a major environmental concern in sustainable agriculture. Conventional methods for measuring and controlling these emissions are manual, time-consuming, and lack predictive intelligence, thereby limiting farmers' ability to make timely, data-driven decisions. This paper addresses these challenges by integrating IoT-based sensing and AI-driven predictive analytics to enable real-time data acquisition, intelligent forecasting, and emission control for livestock management. The IoT subsystem, designed and simulated in Proteus, comprises a methane gas sensor, an ATmega328P microcontroller, an ESP8266 Wi-Fi module, and a cloud-based Blynk dashboard. Simulation results confirmed stable data transmission, accurate methane detection across varying concentrations, and real-time visualization on a mobile interface. The AI component utilized a comprehensive dataset of feed composition, animal weight, and environmental variables collected from ruminant farms across South–South Nigeria. Three supervised learning algorithms, Random Forest, XGBoost, and Artificial Neural Network (ANN), were retrained and evaluated using performance metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The Random Forest model outperformed the others with MAE = 1.52, RMSE = 2.21, and predictive accuracy of 93%. The integrated AI–IoT system demonstrates the ability to monitor methane emissions continuously, predict future trends, and generate actionable insights to optimise feed strategies and livestock performance. This hybrid approach contributes to greenhouse gas mitigation, precision livestock management, and environmental sustainability in modern agriculture.***

Keywords*: Artificial Intelligence, Internet of Things, Methane Emission, Sustainable Ruminant Farming, Machine Learning*

Nomenclature:
GHG: Greenhouse Gas
AI: Artificial Intelligence
IoT: Internet of Things
RMSE: Root Mean Squared Error
ANN: Artificial Neural Network
MAE: Mean Absolute Error
ADC: Analogue-To-Digital Converter
ADL: Acid Detergent Lignin
NDF: Neutral Detergent Fibre
DM: Dry Matter
CP: Crude Protein
CF: Crude Fibre
RF: Random Forest
IQR: Interquartile Range
MQTT: Message Queuing Telemetry Transport
CoAP: Constrained Application Protocol

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I. INTRODUCTION

Methane emissions from ruminant livestock, such as cattle, sheep, and goats, pose a major environmental challenge in modern agriculture. Methane is a potent greenhouse gas with a global warming potential more than 25 times that of carbon dioxide, contributing significantly to agricultural greenhouse gas (GHG) emissions. Traditional measurement methods lack real-time capabilities and predictive intelligence, limiting farmers' ability to manage emissions effectively.

Recent advances in the Internet of Things (IoT) and Artificial Intelligence (AI) have transformed the agricultural landscape, enabling data-driven precision livestock management. IoT facilitates continuous sensing and transmission of environmental and biological data, while AI provides predictive analytics and optimisation to improve decision-making. Integrating these technologies creates a powerful framework that can monitor methane emissions, predict future trends, and guide mitigation strategies. This research aims to design and implement an AI-enabled IoT framework that provides both real-time methane emission monitoring and predictive analytics to support sustainable ruminant farming. By combining IoT hardware with AI models, the framework enhances emission control, feed efficiency, and overall farm productivity.

II. REVIEWED RELATED WORKS

Previous studies have explored various dimensions of methane monitoring and prediction. In [1], IoT-based environmental monitoring systems were examined, emphasizing their utility in air and water quality management. In [2], the potential application of low-cost gas sensors to monitor enteric methane emissions from ruminant animals was proposed, while [3] analysed sensor data to optimise methane leakage detection and mitigation. AI-driven approaches have also been investigated. In [4],

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ensemble and hybrid machine learning models for methane prediction were evaluated. Forecasting methane data using multivariate long short-term memory neural networks was addressed in [5], while [6] applied reinforcement learning to agricultural fertilisation and irrigation, accounting for emissions [7]. Explored blockchain-secured IoT frameworks to enhance data reliability in smart farming and ensure transparency in emission reporting. A cloud-based livestock management system integrating IoT sensors and AI models to improve feed utilization and reduce methane intensity per animal was developed in [8]. Similarly, [9] conducted a review and presented advances in estimating methane emissions from livestock through data collection and AI techniques to improve farming.

In [10], the integration of IoT and AI for greenhouse gas tracking in mixed farms, highlighting their complementary potential, was explained in depth [11]. Presented advancing precision livestock farming by integrating AI and emerging technology. Furthermore, [12] designed an IoT-enabled device for real-time monitoring of greenhouse gas emissions in anaerobic reactors, showing a strong correlation between sensor-based estimates and measured data. In [13], a spatiotemporal prediction of carbon emissions using a hybrid deep learning model considering temporal and spatial correlations was presented.

While these studies contribute significantly to methane emission tracking and prediction, most existing systems treat IoT-based monitoring and AI-based analytics as independent processes. Few provide an integrated framework capable of both real-time sensing and predictive intelligence for proactive emission management. This study addresses that gap by developing a unified AI-enabled IoT framework that monitors methane emissions in real time and predicts future trends to guide sustainable livestock operations.

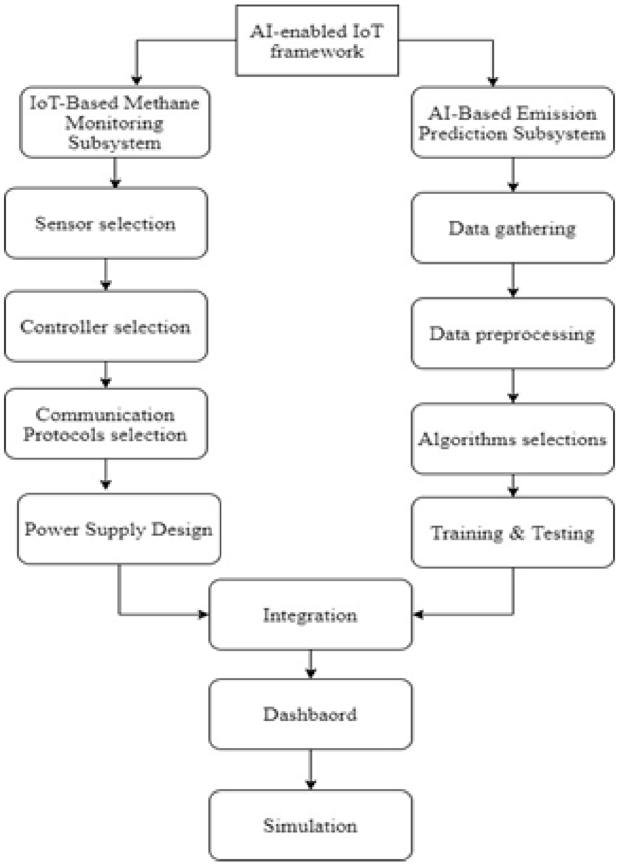
III. SYSTEM METHODOLOGY

A. System Design Approach

The AI-enabled IoT framework comprises two major components: the IoT-Based Methane Monitoring Subsystem and the AI-Based Emission Prediction Subsystem. The overall system architecture integrates field-deployed sensors, microcontrollers, cloud-based analytics, and a web dashboard for visualisation, as shown in Fig.1.

B. IoT Subsystem Design

The IoT subsystem for methane emission monitoring was developed using a top-down design approach and simulated with Proteus software to validate its functionality. The system comprises several key components that work together to ensure accurate sensing, processing, and transmission of data. At its core is the methane gas sensor, which detects the concentration of CH_4 in the ruminant's environment and converts it into an electrical signal proportional to the gas level. This signal is received by the ATmega328P microcontroller, which processes the data and manages communication with the cloud platform. To enable wireless connectivity, the ESP8266 Wi-Fi module was integrated into the design, allowing the processed data to be transmitted seamlessly to an online server. The cloud-based Blynk platform serves as the system's visualisation and storage interface, providing real-time monitoring, data analysis, and alert notifications to the user via mobile devices. A dedicated power supply unit delivers a regulated 5V to all system components, ensuring stable operation and energy efficiency. Sensor readings are transmitted continuously to the cloud for real-time analysis, and warning alerts are automatically generated whenever methane levels exceed predefined safety thresholds. The system's functional layout is represented in the block diagram shown in Fig.2, while the detailed simulated circuit configuration is presented in Fig.3.



[Fig. 1. AI-Enabled IoT System Architecture]

The architecture of the IoT system for ruminant monitoring is illustrated in Figure 3. During operation, the main control switch (SW1) is turned on, activating the two 7805 voltage regulator modules (U7 and U8). These modules convert the 7.4V output from the lithium-ion rechargeable battery to a stable 5V supply required by other components of the system. This voltage regulation ensures consistent power delivery for reliable system performance. Signals from the sensors are fed into the microcontroller's analogue-to-digital converter (ADC) section. The sensors detect methane.

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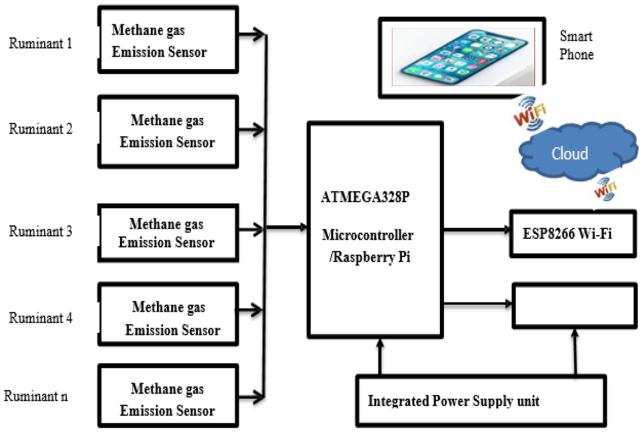
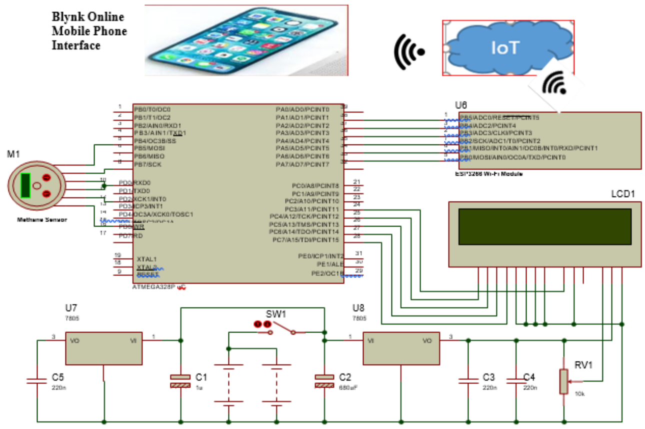


[Fig.2: Block Diagram of Methane Monitoring Subsystem]

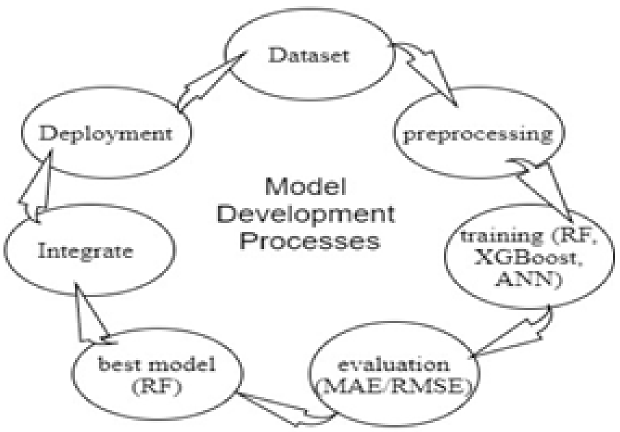


[Fig.3: Proteus Simulation Circuit for Methane Detection]

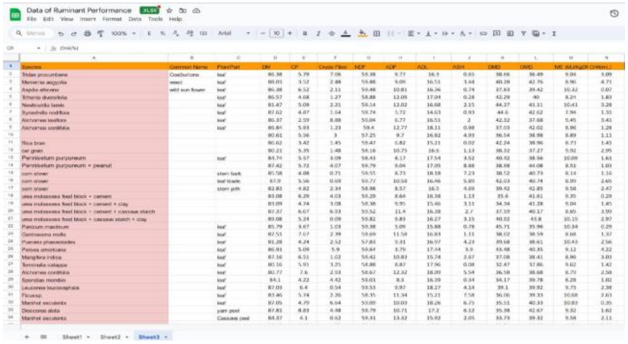
The controller processes concentrations in the ruminant environment and the resulting voltage signals to compute key feed composition parameters such as Neutral Detergent Fibre (NDF), Dry Matter (DM), Crude Protein (CP), Acid Detergent Fibre (ADF), Acid Detergent Lignin (ADL), ash content, and methane concentration. These computed values are transmitted to the cloud-based Blynk platform, an IoT service used for real-time visualization and further data processing and subsequently forwarded to the end user's mobile device for monitoring and analysis.

C. AI Model Development

The Model development strictly follows the step-by-step process shown in the diagram of Fig.4.



[Fig.4: AI Model Development and Training Process]



[Fig.5: Dataset Features for Methane Emission Prediction]

Methane emission data were obtained from various agricultural research institutes across the South–South region of Nigeria and from publicly available databases. The collected datasets spanned 2019 to 2024 and included comprehensive variables such as feed composition, environmental conditions, and herd demographics. In total, more than 1,000 data records were gathered, pre-processed, and compiled, providing a diverse and representative sample for model training and evaluation. These datasets encompassed multiple factors known to influence methane emissions in ruminant livestock, forming a reliable foundation for developing and validating the machine learning models used in this study. The dataset included chemical parameters such as Dry Matter (DM), Crude Protein (CP), Crude Fibre (CF), Neutral Detergent Fibre (NDF), Acid Detergent Fibre (ADF), and Acid Detergent Lignin (ADL), recorded in Microsoft Excel (Fig. 5).

D. AI Model Training Processes

The research employed three supervised machine learning algorithms: Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Artificial Neural Networks (ANN) to predict methane emissions from ruminant livestock. Each model was trained and evaluated on the same dataset, split into 80:20 for training and testing, respectively. The Random Forest algorithm was configured with 100 decision trees and a maximum tree depth of 10. Feature selection was performed using the Gini impurity criterion to identify the most influential variables affecting methane emission levels. Random Forest was selected for its robustness to both continuous and categorical data and its resistance to overfitting on moderately sized datasets. The XGBoost model was implemented with a learning rate of 0.1, a maximum tree depth of 6, and 1,000 estimators.

E. Data Preprocessing and Feature Engineering

The collected datasets underwent a thorough preprocessing stage to enhance model accuracy and ensure consistency across heterogeneous data sources. Missing values in feed composition and environmental parameters were handled using mean imputation for continuous variables and mode substitution for categorical entries. Outlier detection was performed using the interquartile range (IQR) technique to remove spurious sensor readings. Numerical features were normalized using Min–Max scaling to maintain uniform feature magnitudes, while categorical data such as feed type were label-encoded to make them machine-readable.

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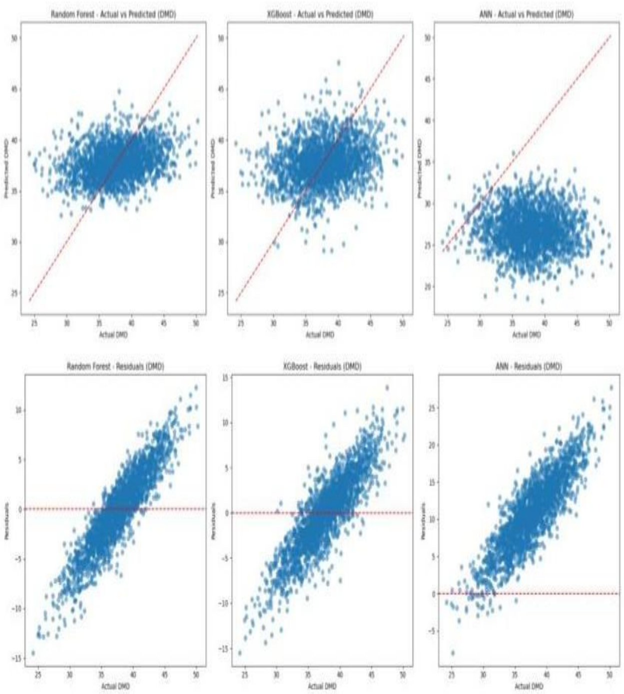
Feature correlation analysis using Pearson's coefficient helped identify redundant variables and retain the most influential parameters (DM, CP, NDF, and ADF) for model training.

To enhance model accuracy, grid search cross-validation was used to fine-tune key hyperparameters, including learning rate, maximum depth, and the number of estimators. XGBoost was preferred for its high computational efficiency, its ability to handle imbalanced datasets, and its consistent performance in predictive modelling competitions.

The Artificial Neural Network (ANN) architecture comprised three hidden layers, each containing 50 neurons, and utilised the Rectified Linear Unit (ReLU) activation function. The output layer consisted of a single neuron with a linear activation function to predict methane emission values. The ANN model was trained using the Adam optimiser with a learning rate of 0.01, and early stopping was implemented to prevent overfitting. The ANN approach was adopted for its strong capability to capture complex, non-linear relationships among input features, particularly when interactions between feed composition and environmental parameters influence emission outcomes.

F. Integration Framework and Model Testing

The final framework integrates the IoT subsystem and AI model. Real-time data from IoT sensors feed into the AI module hosted in the cloud, which continuously predicts methane emissions and visualises insights via a web dashboard.



[Fig.6: Comparative Performance Scatter Plots for RF, XGBoost, and ANN]

After training, each machine learning model was evaluated on the reserved 20% of the dataset to assess its generalisation performance. Model evaluation was carried out using standard statistical metrics, including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), to quantify prediction accuracy and deviation from actual values. The comparative error analysis for the three models, Random Forest, XGBoost, and Artificial Neural Network, is illustrated in Fig. 6. The scatter plots show the relationship between predicted and actual methane emission values, providing a clear visual representation of each model's predictive capability. The proximity of the data points to the red dashed reference line indicates the degree of accuracy, with points closer to the line signifying stronger model performance and better alignment with real observations.

IV. RESULTS OBTAINED

A. IoT Simulation

The Proteus simulation confirmed successful integration of all components. The methane sensor accurately detected varying CH_4 concentrations, and Wi-Fi data transmission to the Blynk server was stable. The dashboard displayed real-time readings and alert notifications.

B. AI Model Performance

Among the three models tested, the Random Forest (RF) algorithm demonstrated the best overall performance, producing the lowest error metrics and the highest predictive accuracy. The model achieved a Mean Absolute Error (MAE) of 1.5780, a Root Mean Squared Error (RMSE) of 5.3568, and an overall prediction accuracy of approximately 93%, as shown in Table I. These results indicate that the Random Forest model was highly effective in capturing the complex relationships among the input variables and methane emission levels. Further feature importance analysis revealed that feed composition parameters, particularly dry matter, crude protein, and fibre content, as well as livestock body weight, were the most influential factors in determining methane output. This insight highlights the critical role of dietary formulation and animal physiology in emission dynamics. The trained Random Forest model was subsequently integrated into the IoT framework to enable real-time methane emission forecasting. Through this integration, continuous sensor data from the IoT subsystem were fed directly into the AI model hosted on the cloud, allowing for automatic prediction and visualization of emission trends. This configuration empowers farmers to implement proactive management strategies, such as adjusting feed composition or modifying herd conditions, thereby minimizing methane output and enhancing the sustainability of ruminant production systems.

Table I: Comparative Performance of Machine Learning Models

Model	MAE	RMSE	Accuracy (%)
Random Forest	1.58	5.36	**93.0**
XGBoost	2.12	6.28	89.4
ANN	2.45	6.87	86.7

The superior performance of the Random Forest model can be attributed to its ensemble learning mechanism, which combines multiple decision trees to minimize variance and prevent overfitting. Unlike single estimators, the averaging of multiple trees enhances robustness and improves generalization across varying farm conditions. This makes Random Forest particularly well-suited for heterogeneous

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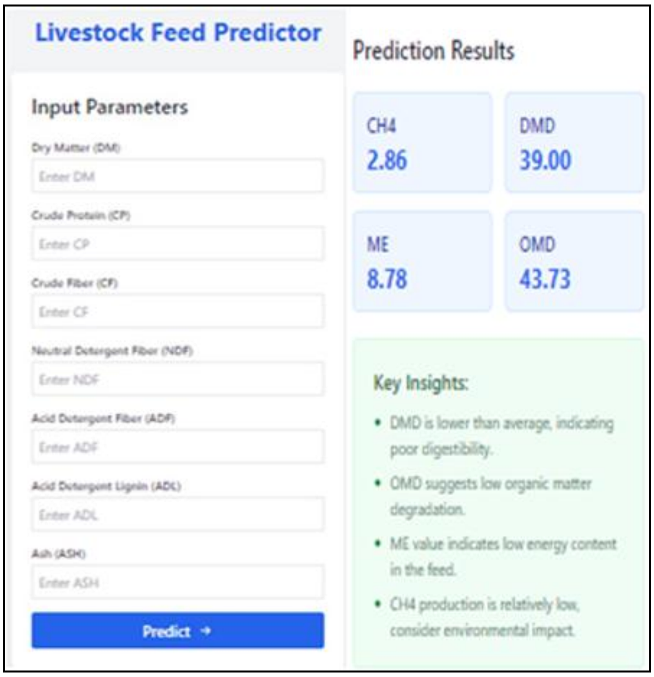
agricultural datasets that include nonlinear and interacting variables such as feed composition and environmental factors.

C. Web-Based Methane Emission Predictor

A web-based application was developed to facilitate the testing and validation of the Random Forest model**,** which demonstrated superior predictive performance. The web application interface is shown in Fig. 7. During testing, users enter parameters such as feed composition and related environmental variables into the designated fields, then click the Predict button to generate and display the corresponding methane emission estimates.



[Fig.7: Web-Based Methane Emission Prediction Interface]

V. CONCLUSION

This study presented an integrated AI-enabled IoT framework designed to monitor and predict methane emissions in ruminant farming environments. The system successfully merged real-time data acquisition with intelligent predictive modelling to support sustainable livestock management. The IoT subsystem provided continuous sensing and reliable cloud-based data transmission, enabling farmers to visualize emission levels remotely. On the analytical side, machine learning models were developed to forecast methane trends based on environmental and animal-related variables, with the Random Forest algorithm demonstrating the most consistent accuracy and stability across multiple evaluation metrics. The synergy between the IoT monitoring layer and the AI prediction model establishes a robust platform for data-driven emission management in livestock production. By providing actionable insights, the framework enables early intervention, improved feed optimization, and better environmental compliance, aligning agricultural practices with global sustainability goals.

Despite promising simulation and modelling results, the practical deployment of the AIoT framework faces challenges, including inconsistent rural network connectivity, sensor calibration drift in harsh farm environments, and limited access to cloud computing infrastructure in remote areas. Future work should explore edge-AI implementations and lightweight protocols (e.g., Message Queuing Telemetry Transport (MQTT), Constrained Application Protocol (CoAP) to ensure reliability under constrained conditions and enhance scalability across diverse farm sizes.

DECLARATION STATEMENT

The Authors hereby include a declaration of accountability in our article based on individual contributions and respective expertise.

As the article's author, I must verify the accuracy of the following information after aggregating input from all authors.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted objectively and without external influence.
- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

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