International Research Journal of Innovative Engineering (IRJIE)

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

Interpretable Machine Learning Approaches for Fault Diagnosis and Predictive Maintenance in EV Powertrains

Shashikala Valiki

Independent Researcher, Canada

shashikala.valiki.researcher@gmail.com

Sophia Müller

Junior Research Assistant, Rhineburg Institute of Applied Sciences, Germany

sophiamullerr@outlook.com

Publication History: Received: 20.05.2025; Revised: 25.06.2026; Accepted: 30.06. 2026; Published: 13.07.2026

ABSTRACT: Cape Verde, an archipelago in the Central Atlantic, is confronted with opportunities and challenges associated with the development of business and tourism sectors, including the root and tuber value chains. This phenomenon is associated with climate change that increasingly dictates new business opportunities and new risk factors to be addressed in the world of tourism. This study identified risk scales associated with climate change along the entire root and tuber value chain in the country. In addition to these factors, 85 positive and negative risk factors were identified, classified and described. A set of thematic maps was built, presenting the risk levels and their factors in Cape Verde and in each of the six islands that make up the country. The research indicated that drought and desertification are the most critical climate risks on the islands. The lower development of the root and tuber tourism value chain in Cape Verde offers new opportunities for businesses and tourism. The analysis of the initialized risk factors in the root and tuber value chain provides the foundation for implementing a climate risk management plan, which seeks to minimize, decrease and/or mitigate the consequences for tourism due to the effects of climate change.

KEYWORDS: Electric vehicles, powertrains, predictive maintenance, explainable artificial intelligence, diagnostics, prognostics, battery management system, thermal management, electric motor and inverter, safety-critical applications.

I. INTRODUCTION

Predictive maintenance techniques are increasingly used in electric vehicles (EVs) to ensure reliability and safety, and to reduce maintenance costs and associated vehicle downtime. A large number of sensors generate extensive amounts of data that powertrain computers use for system management, diagnostics, and fault prediction. The availability of maintenance-related data recorded by vehicles in the field presents an opportunity to develop artificial-intelligence-based solutions for predictive maintenance. Such machine-learning and deep-learning models can predict the imminent failure of components, enabling proactive maintenance action.

For deployment in safety-critical applications, however, these models must meet explainability requirements. Meaningfully explaining the model's reasoning increases user trust in its predictions and supports operation and maintenance. Unlike failure prediction, which classifies the operational condition, the aim of system-level diagnostics is to explain the model's predicted class while offering auxiliary fault indicators. Beyond simple fault codes, the objective is to provide detailed explanations clarifying how symptoms and other evidence point to the faults. A generic architectural design applicable to different subsystems is proposed first, followed by a comparison of methodologies for generating explanations. Domain-specific frameworks for battery, motor, inverter, thermal management, and other powertrain systems are then established.

1.1. Background and Significance: The strategic and regulatory push to decarbonize road transportation underscores the need for electric vehicle powertrains that are economically viable, safe, and reliable. Battery-electric and fuel-cell

International Research Journal of Innovative Engineering (IRJIE)

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

vehicles constitute a new and rapidly growing vehicle category that relies on sophisticated electric components and systems. Large volume manufacturers (OEMs) have established predictive maintenance (PM) programs for their global fleets by leveraging the rich data streams made publicly available through dedicated in-vehicle telecommunications systems. However, due to the complexity, cost, and safety-critical nature of electric powertrains, these OEMs do not provide sufficiently reliable prognoses for the major electric components and systems outside PM manuals, leaving aftermarket service providers to rely on traditional time-based maintenance schedules. Consequently, maintenance predictive capabilities for electric vehicle powertrains have received limited academic attention when compared to these OEMs' proprietary solutions.

For critical and complex components such as batteries, electrical machines, power electronics, and thermal/thermal-management systems, prognosis with sufficient reliability is particularly challenging but required to enable safe and cost-effective electric-vehicle operation. Basic supervision-free data-driven diagnostics approaches apply equilibrium-based models or deep neural networks without the rigor of normal operation. Key real-world failure modes continue without automated prediction, and vendor-provisioned diagnostic trouble codes are not supplemented by explanation. A more comprehensive, structured, and modular framework for explainable diagnostics with a particular focus on prognostics is required.

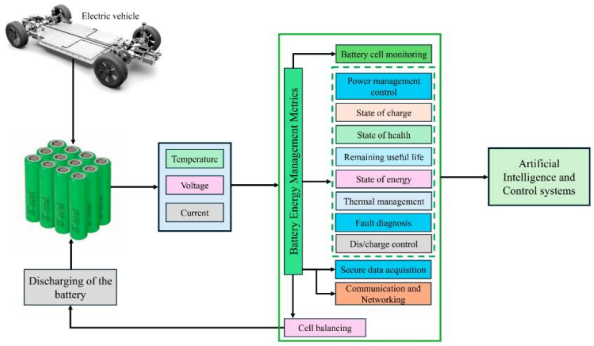


Fig 1: Next Generation of Electric Vehicles

1.2. Research design: The main objective is to lay a formal foundation for applying explainable artificial intelligence (XAI) to diagnostic systems for predictive maintenance (PM) in EV powertrains. The underlying hypothesis states that enabling PM diagnostics systems with appropriate explanations will help alleviate the current synthesis and evaluation challenges and support industry adoption. Although the adoption of PM principles in EV powertrains has received considerable attention, a systematic approach that explicitly leverages XAI techniques and considers the specific operational and industrial contexts has not been fully articulated. To support this analysis, a two-staged XAI workflow is proposed. The first stage identifies and classifies a PM use case based on a chosen failure mode and the resources required to support the predictive model, while the second stage provides tailored explanations according to the XAI principles most relevant to the application.

A comprehensive performance assessment and comparison of different explanation mechanisms for a given PM use case and predictive model can often be challenging. Indeed, although machine learning (ML) and deep-learning models commonly outperform interpretable approaches in predictive accuracy, they sometimes do so at the expense of local or global human interpretability. The selection of an explanation technique and its configuration normally reflect critical attributes of the use case considered rather than the nature of the model. Thus, in cases where the model accuracy is paramount, and attention can be devoted to the explanations during the evaluation phase, a model-agnostic selection might be preferred. Conversely, for applications in safety-critical domains, or where explanation quality is essential, careful specification of the model-agnostic explanation mechanism and model choice may yield valuable insights.

II. BACKGROUND AND THEORETICAL FOUNDATIONS

Residual Analysis, Data Dimensionality Reduction, and Random Sampling—Statistical Data Handling for a Predictive Maintenance Application Residual analysis is a technique utilized to evaluate whether a fitted model is suitable. The residuals from modeling the difference between the dependent variable and the predicted values are expected to satisfy specific conditions, including:

International Research Journal of Innovative Engineering (IRJIE)

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

The residuals must be randomly spread around the centerline.
The residuals must be normally distributed.
The residuals must be independent of each other.
The residuals must exhibit constant variance.

If the residuals do not conform to these conditions, the model is not optimal. A linear regression model, for instance, may fit the data well, producing a low RMSE; however, it may still not be appropriate if the residuals exhibit clear patterns, are non-normally distributed, are not independent, or show non-constant variance.

In many real-life problems, the dimensionality of the dataset is high. Reducing data dimensionality typically helps improve model performance and avoid overfitting. High-dimensional datasets also lead to longer execution times. Random sub-sampling can help reduce data volume while achieving similar modeling quality. For example, for large datasets, applying random sampling to select only 20% of the data can often improve execution speed without degrading model performance quality.

2.1. Predictive Maintenance in Electric Vehicle Powertrains: Predictive maintenance aims to predict failures before they occur to minimize unplanned downtime and maintenance costs. Although it is widely used in various domains, the absence of a predictive-maintenance framework for electric vehicles hampers reliable and safe operations that meet public expectation and industry requirements. Evidence that predictive maintenance succeeds in other applications does not necessarily guarantee that it can be applied to electric vehicle powertrains. Open questions concern the causes of electric vehicle outages, the dominant mode of electric vehicle failures, the data required for effective predictive-maintenance models, and their performance evaluation metrics. Answering these questions not only adds to an understanding of electric vehicle reliability but also supports the development of predictive-maintenance solutions for this rapidly growing area of transportation.

The operational reliability of electric vehicles greatly depends on the underlying powertrains, which are susceptible to various faults and failures. Nonetheless, detailed investigations of electric vehicle failures remain scarce. A study of the operational reliability of vehicles in the Automotive Information Sharing and Analysis Center database revealed that batteries are the most frequently cited lesions, followed by connector issues and electrical harnesses. A comprehensive study of incident reports data from the National Highway Traffic Safety Administration found that inadequate battery design increases the risk of fire and smoke, battery management system flaws may lead to undetected overheating, and electric motors and inverters are vulnerable to thermal issues. These results suggest that battery degradation, auxiliary connector issues, and electric motor and inverter defects are the main causes of electric vehicle failures.

Equation 1: Residual analysis (model adequacy) — full derivation
For data points (x_i, y_i) and a fitted model prediction $\hat{y}_i$:
1. **Prediction**: $\hat{y}_i = f(x_i)$
2. **Residual** (error at sample i):

$$e_i = y_i - \hat{y}_i$$

Start from "average squared error":
1. Square each residual: e_i^2
2. Sum across all n samples: $\sum_{i=1}^{n} e_i^2$
3. Divide by n to average:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} e_i^2$$

RMSE is just the square root of MSE so it's in the same units as y:

$$\text{RMSE} = \sqrt{\text{MSE}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2}$$

- **Residuals vs fitted**: check "randomly spread around centerline (0)"
- **Histogram / normality check**: check "normally distributed"
- **Independence**: residuals over time / lag plot
- **Constant variance**: look for "fan shape" or heteroscedasticity

International Research Journal of Innovative Engineering (IRJIE)

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

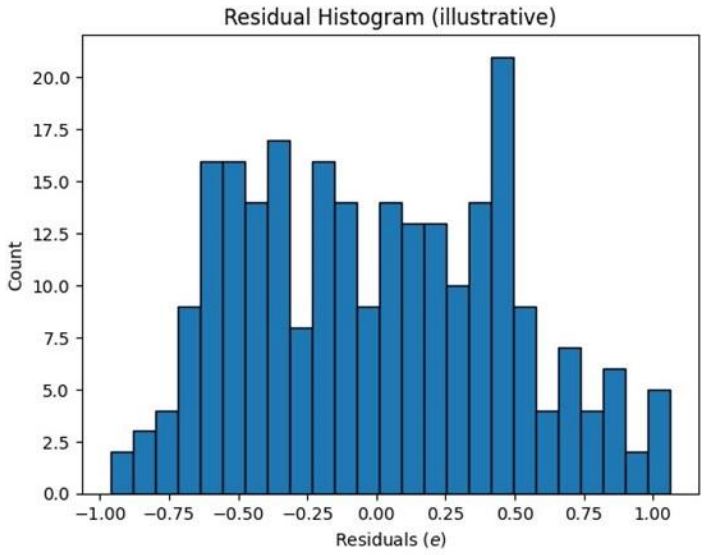
DOI:10.15680/IRJIE.2026.1004006

2.2. Explainable Artificial Intelligence: Concepts and Techniques: Explainable Artificial Intelligence (XAI) refers to methods or applications of AI whose results can be understood and interpreted by a human. Within this definition, explainable can have different meanings. Explainable is closely related to the desirable feature of interpretability defined by Lipton, namely "the degree to which a human can understand the cause of a decision". Two kind of interpretations can be considered: local interpretations (which explain individual predictions) and global interpretations (which explain the overall behaviour of the model). Moreover, it should be noted that not all models of AI are prone to interpretation. In fact, "deep learning models or black-box models in general are extremely powerful, accurate and successful in many areas, but still hard to interpret, whereas interpretable models are usually simpler, with lower prediction performance". When there is a desire of interpretability, a complex model is trained and after that efforts are made to understand the model's decision by employing other explicable methods.

Interpretability and transparency of the AI-based models belong to a particular aspect of the risk management cycle as far as safety-critical contexts are concerned. Transparency within a safety-critical sense means that "the safety and assurance arguments presented for the AI application are essentially correct and the relevant characteristics/behaviours of the system modelled by the AI services are adequately understood to support appropriate decisions". Therefore, all AI solutions supporting or replacing parts of human decision-making in safety-critical contexts must be sufficiently transparent and interpretable to justify the associated risks. Interpretability and explainability of AI applications are also considered in ethical AI and AI governance contexts, given that explainable AI is a principle included in the OECD Principles on AI.

2.3. Diagnostic Models and Data Sources in EV Powertrains: Diagnosis relies on a range of machine Learning (ML), statistical, and physics-based models. A core aspect of these models is the data used as input and the information leveraged to label failure modes. Similarly, the precise sensors and components involved in failure detection and what information from them is deemed important also varies depending on the nature of the failure. Therefore, in this section, the telemetry, dataset characteristics, sensors, and auxiliary information frequently employed in EV powertrain diagnostics are summarized.

The data selected to model normal and faulty conditions must accurately represent the behavior of the system or component under evaluation. Indeed, Real-World Data from vehicles in the field naturally contain the noise and incompleteness usually present in real applications. By contrast, synthetic data rely upon a model — often physics-based — that is valid within the given operating range and always supervised and labelled. The telemetry information can also be limited to a small subset of sensors. Diagnostic tasks on safety-critical components often exploit data from different parts of the EV powertrain. In these instances, the models can thus be expressed as a function of time, where time-series-related techniques are leveraged — often leading to better performance compared with conventional static classification techniques. Another common requirement is that fault codes emitted by the BSM are available; these codes may require a supervised procedure to assess their explanatory and diagnostic power.



International Research Journal of Innovative Engineering (IRJIE)

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

III. ARCHITECTURE OF EXPLAINABLE DIAGNOSTICS SYSTEMS

The architecture of a system for generating explainable diagnostics is designed to facilitate the disclosure of information surrounding the reliability of a given decision, prediction, or assessment. Although specific to an explainable framework for predictive maintenance in electric vehicle powertrains powered by deep learning, these concepts are relevant to prognostic models in general. Effective predictive maintenance offers significant quality-of-life improvements for end users by reducing downtime. Furthermore, when applied to safety-critical subsystems such as thermal management, explainable predictive maintenance systems can project the condition of the underlying system, allowing users to take action before a catastrophic failure occurs.

The proposed system receives input from engineering models, various sensors, and historical maintenance records pertaining to the vehicle in question. A preprocessing module collects data from the sensors and analytics systems, synchronizes the datasets, and removes outliers. A feature-extraction module extracts the necessary features for each model, which are commonly weather data, operation time, ground temperature, thermal-status gauges, and fault codes from the battery management system. Given the safety-critical nature of the application, privacy is preserved by removing the metadata associated with the telemetry data, including indexes and packet timestamps, before model training.

Many explainability techniques can be linked to a specific type of user. For instance, feature importance scoring can aid the understanding of black-box models by identifying key inputs, thereby offering a high-level overview of the decision-making process. Model-agnostic local perturbation methods such as LIME and SHAP provide model-agnostic local explanations and are useful for users interpreting individual predictions, including subject-matter experts who may inspect a sample of explanations to interpret a multitude of predictions. Other techniques focus on providing more qualitative causality-based global explanations. Diagnosis and maintenance personnel are often the justifications' primary audience, as both rely heavily on the diagnoses made by the system. Mostrar mais.

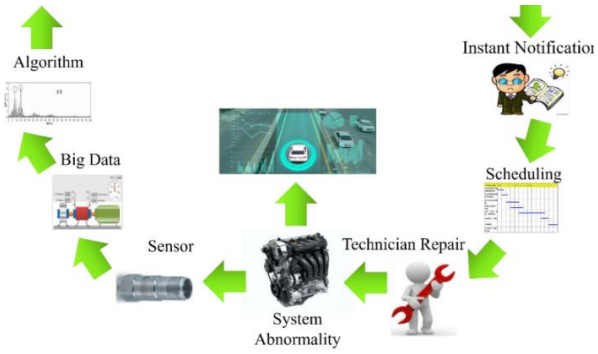


Fig 2: Architecture of Explainable Diagnostics Systems

3.1. Data Acquisition and Preprocessing: Data acquisition and preprocessing, essential for all data-driven predictive maintenance approaches, encompass data collection, synchronization, cleaning, feature extraction, and privacy considerations. Available data sources encompass telemetry data from onboard sensors, third-party driving datasets, fault codes, and degradation indicators. Telemetry data from remote sensors such as the Nordic Sensor Dataset and Driving Dataset in Northern China capture driving patterns, conditions, and power consumption. Labels reflecting extreme working conditions guiding battery degradation, excessive wear of brake systems and tires, and state variations of the cooling system are also included, serving as potential sources for long-term predictive maintenance models although never shared in the past. Ongoing efforts expressed in special issues related to an appropriate marketing dataset for electric vehicles reflect the growing research interest.

The lack of a complete set of driving data of a specific car brand makes a tailored dataset impossible. Nevertheless, data of a different brand can be used for training, and transfer learning strategies can be applied when a small amount of target data emerges. Data from braking wear testing can also serve as labels. However, due to the limited quantity, a statistical transfer learning approach is applied on these labels. Driving data collected at a relatively high frequency is also available, providing training and test data for wear prediction with unsupervised training. Data from OEM telemetry and from the

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

industry development and maintenance network can also be leveraged to build predictive maintenance models, although appropriate action is required to ensure data confidentiality.

3.2. Predictive Models for Failure Prediction: Candidate models for automating failure prediction encompass statistical, machine-learning, and deep-learning alternatives. Statistical methods provide interpretable results with low computational demands, especially attractive for small datasets. However, such datasets are inherently limited in the context of predictive maintenance because real-world failures seldom occur. Classically used algorithms like logistic regression and linear discriminant analysis offer insights into the goodness of fit but do not naturally support future risk estimation. Machine-learning algorithms, such as random forests and support-vector machines, can generate confidence measures (through, e.g., probability estimates) and usually outperform statistical methods. More recently, neural networks have been exploited for failure prediction. Their capacity to handle multivariate time series makes them ideal for such applications. Drawbacks include the potential need for vast amounts of training data, excessive training times, possible proneness to overfitting, and the limited interpretability of their predictions. In fact, due to their black-box nature, neural networks remain largely unsupported in safety-critical contexts.

All considered predictive models ultimately yield a risk score, indicating the likelihood of failure within the horizon of interest. Such ranges (decreasing likelihood with increasing distance) are informative and allow decision-makers to trade off response latency and cost sensitivity. Depending on the model employed, these risk estimates can be complemented by a degree of confidence, providing valuable additional information when triggering maintenance actions.

3.3. Explainability Mechanisms and Interfaces: Methods for generating explanations must accommodate their intended recipients, incorporating task- or user-specific perspectives and formats. The design of user interfaces should take user characteristics into account, such as specific knowledge, expertise, goals, and cognitive limitations, and explanations must thus be tailored to specific persons and contexts. Supporting decision-making requires connecting explanation delivery with the user's task and providing information that is useful for the completion of that task. The specific data and explanations presented to end users should differ from those supplied for other purposes, such as system monitoring or explanation validation. Even though the underlying models may be complex and difficult to understand, the system may still be interpretable if appropriate explanations can be provided.

IV. METHODOLOGICAL FRAMEWORKS FOR EXPLAINABLE DIAGNOSTICS

Two concepts often come into play when discussing approaches to an explainable AI-driven diagnostic system: model-agnostic versus model-specific explainability and integration of temporal or causal reasoning. The first relates to whether the diagnostics consider a family of models capable of producing interpretable predictions, which opens the door to a wider range of practical applications, or whether the explainability function is instead crafted around a single, often more complex model, which may offer better-quality configurational or topological statements. The second highlights the importance of handling time-series data in a way that exploits fault progression over time or provides causal explanations of the model output (e.g., main indicators of confidence loss), explanatory factors for the detected fault prediction, and insight into which specific fault is most probable.

In some contexts, particularly safety-critical applications, exploration of the ontological foundation of the component under diagnosis—in other words, what happens inside the component itself—can also shed light on the causes and effects of failures, and consideration of how such knowledge can be embedded in the explainability function may be valuable. Another key area in the quest for safety and reliability resides in uncertainty quantification; aleatoric and epistemic uncertainty in model predictions must be assessed to ensure that actions and decisions based on diagnostic conclusions are properly calibrated. Integrating uncertainty quantification into an explainable diagnosis maintains the alignment of explainability with trust, offering intuitive risk interpretation while providing a basis for future research on safe-fail, risk-aware controllers in the diagnosis loop.

4.1. Model-Agnostic Versus Model-Specific Explainability: Explainable AI techniques can be classified into model-agnostic and model-specific methods. Model-agnostic techniques can be used in conjunction with any predictive model, while model-specific techniques are tailored to a particular class of models. This distinction affects the applicability, advantages, and limitations of different methods.

Model-agnostic techniques can be applied to any predictive model regardless of its architecture, thus supporting the interpretability of black-boxes. However, the explanations generated by such techniques are usually faithful only locally

International Research Journal of Innovative Engineering (IRJIE)

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

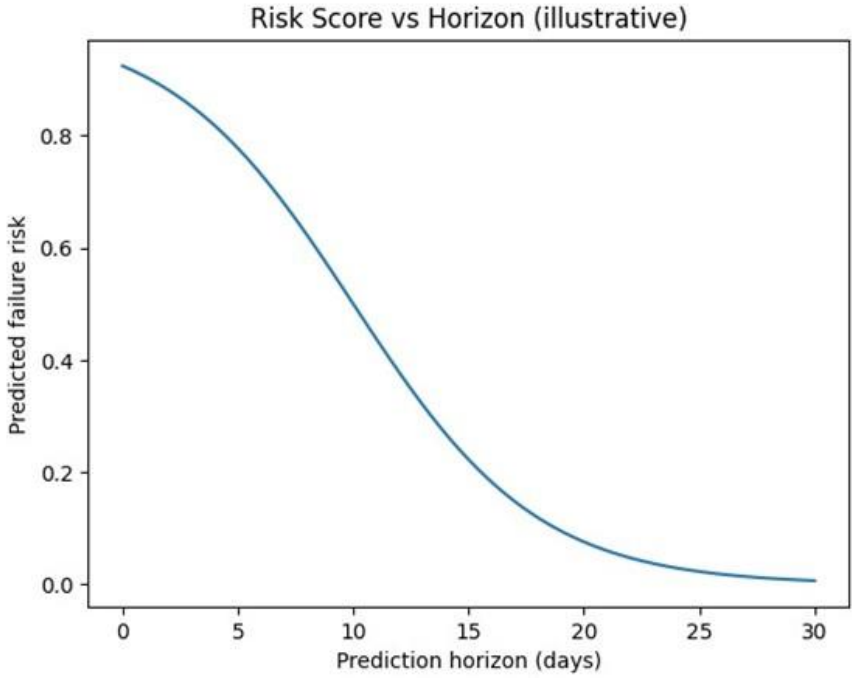
DOI:10.15680/IRJIE.2026.1004006

and approximately. Examples include Local Interpretable Model-agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP). LIME fits an interpretable, local surrogate model around a prediction, while SHAP quantifies the contribution of each feature using Shapley values from cooperative game theory.

Model-specific techniques, on the other hand, exploit the characteristics of a specific predictive model to generate global and faithful explanations. Such techniques are therefore better suited for safety-critical applications because they improve the understanding of the prediction mechanism. Nevertheless, they cannot be applied to any predictive model and must therefore be used in combination with model-agnostic techniques for black-boxes. Examples of model-specific techniques include Layer-wise Relevance Propagation (LRP), Concept Activation Vectors (CAV), and interpretation methods for decision tree ensembles. LRP propagates prediction scores backwards through the layers of a deep neural network, while CAV quantifies the influence of human-interpretable concepts on the predictions of deep models. Finally, tree ensemble models are intrinsically interpretable because their predictions can be expressed as a set of rules, but their individual predictions can still be interpreted using assignment-based feature influence.

4.2. Temporal and Causal Reasoning in Diagnostics: Temporal reasoning informs the construction and processing of time-series data. Precise timestamps enable evaluations over non-uniform time-steps. When examining length-varying sequences, a padding strategy makes the input and output dimensions fixed. Causal connections are integral to diagnostics, as faults and warnings in a driven system follow the key application timeline. Temporal relationships determine failure modes progression and warrant safety failovers. Causal reasoning exposes temporal relationships through the lens of dependence.

In predictive maintenance, temporal data analysis should account for dynamic relations within the data—specifically, the presence or absence of key indicators that enable failure identification—and, in particular, that operate in non-Markov decision processes relying on action selection and voting mechanisms. Markov networks on temporally-modeled data enable root-cause localization for any failure, while analogy-based fault localization draws from historical data, supporting the explainability prerequisite without requiring probabilistic, optimization, or control-model perspectives.



4.3. Uncertainty Quantification and Confidence Estimation: Both aleatoric and epistemic uncertainty should be treated. Aleatoric uncertainty can stem from inherent stochasticity of the signal (e.g., ambient conditions influencing sensor measurements), while epistemic uncertainty can be associated with lack of enough and diversified data to cover fatigue characteristics on a given motor winding and the consequent need for extensive expert knowledge. Well calibrated

International Research Journal of Innovative Engineering (IRJIE)

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

models are particularly important for forecast confidence quantification. Reliable quantification of uncertainty allows risk-oriented decision support, as higher confidence in a prediction increases readiness for intervention action.

The definition of risk-aware thresholds is linked to risk consideration and fuzzy decision making, but it needs to be done carefully. In cases when a predicted degradation indicator reaching a level that is normally associated with warranty return, in which a failure has high probability within a short time period, a precaution message indicating that even the use of the vehicle in driving conditions related to a given battery's dispatching or use profile should be avoided would be critical for safety, even with remain time above the emergency margin.

Equation 2: Dimensionality reduction via PCA — full derivation
Let the data matrix be $X \in \mathbb{R}^{n\times d}$ (n samples, d features).
For each feature j:
Mean:

$$\mu_j = \frac{1}{n}\sum_{i=1}^{n} X_{ij}$$

Std dev:

$$\sigma_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(X_{ij}-\mu_j\right)^2}$$

Standardized data:

$$X_{ij}^{(c)} = \frac{X_{ij}-\mu_j}{\sigma_j}$$

$$S = \frac{1}{n-1}\left(X^{(c)}\right)^{\top}X^{(c)} \quad \in \mathbb{R}^{d\times d}$$

Solve:

$$Sv_k = \lambda_k v_k$$

- v_k = principal component direction (unit vector)
- λ_k = variance captured along v_k

Sort $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_d$.

$$r_k = \frac{\lambda_k}{\sum_{j=1}^{d}\lambda_j}$$

Cumulative explained variance for first K PCs:

$$R_K = \sum_{k=1}^{K} r_k$$

Let $V_K = [v_1, \ldots, v_K] \in \mathbb{R}^{d\times K}$:

$$Z = X^{(c)}V_K \quad \in \mathbb{R}^{n\times K}$$

(One of the generated plots shows **cumulative explained variance vs number of components**.)

V. APPLICATIONS IN ELECTRIC VEHICLE POWERTRAINS

The core principles of explainable AI (XAI) can enhance predictive maintenance of electric vehicle powertrain components (such as batteries, motors, inverters, thermal units, and power distribution units) if appropriately adapted. In particular, the need for comprehensive, explanation-aware diagnostics that can convey anticipatory, actionable knowledge to users matches the objectives of XAI. These systems provide clear information about detection and predictive-model failures and can thus cover all four diagnostic functions that underpin the notion of intelligent, user-friendly predictive maintenance. The ensuing analysis focuses chiefly on batteries, electric motors, and inverters because XAI techniques for other components well documented elsewhere.

At present, battery management-system diagnostics mainly address the state of health, with a focus on physical degradation indicators, battery-impacting anomalies, XAI-based approaches capable of revealing the reasons behind abnormal cone shape in infrared thermography images of motor windings. Detecting abnormal temperature dynamics through real-time telemetric data of cooling units and using XAI mechanisms to furnish explanations for safety-critical

International Research Journal of Innovative Engineering (IRJIE)

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

alerts about overheating constitute the main open challenges in thermal-management-system diagnostics. Table 5.1 summarizes applications, use cases, and anticipated contributions of XAI-enabled explainable diagnostic models in EV powertrain subsystems.

5.1. Battery Management System Diagnostics: Explainable AI-Driven Diagnostics for Predictive Maintenance in Electric Vehicle Powertrains

Focus on state of health, degradation indicators, and anomaly detection with explanations.
The battery pack in an electric vehicle (EV) is a complex system subject to diverse physical ageing mechanisms, which jointly lead to a gradual decrease in the battery state of health and to the emergence of dangerous failure modes. Explainable Artificial Intelligence (XAI) methods are well-suited to detect critical deviations from the pack's normal behaviour. Investigating open-source battery datasets shows that monitoring auxiliary parameters of the Battery Management System—temperature, electrolyte level, and voltage balance—together with a measure of the degradation rate significantly improves the prediction of pack anomalies. Evidence from modelling and experimentation indicates that such additions help improve model performance and robustness, thus facilitating a more reliable deployment of predictive maintenance bids.

The Battery Management System (BMS) supervises the cell balancing and thermal management of the battery pack, and estimates parameters such as the State of Charge (SoC) and the State of Health (SoH). Moreover, it detects and isolates degradation indicators associated with both slow ageing and sudden failures. Degradation indicators are usually the first factors considered by predictive maintenance strategies, since their reachability and interpretability make them particularly useful. In pure data-driven settings, however, auxiliary chemical and physical parameters—such as the maximum battery cell temperature, electrolyte concentration, level or loss—are often neglected. To determine which auxiliary parameters should be monitored together with key degradation indicators, an analysis based on an open-source battery dataset focused on model interpretability rather than model accuracy.

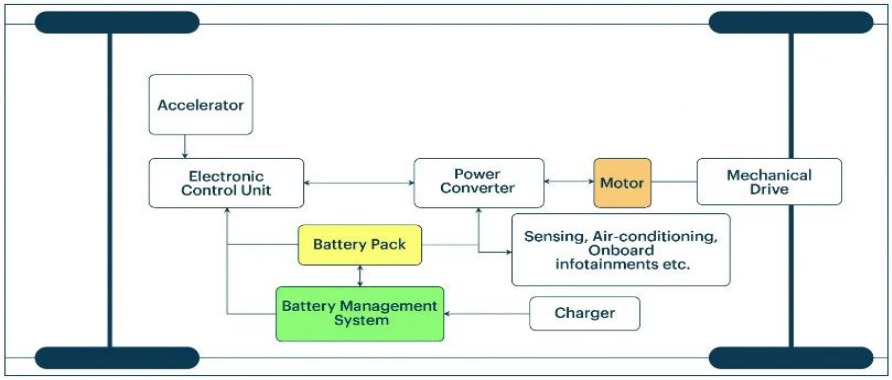


Fig 3: Battery Management System for Electric Vehicles (BMS)

5.2. Electric Motor and Inverter Diagnostics: Windings, thermal, efficiency, and fault-localization diagnostics in EV powertrains are mapped to explainability. Two interrelated sources of faults affect the motor: induction in the rotor due to the stator displacement, fault in phases of the stator windings, and thermal overload. The first induces a transient rotation of the rotor, which may travel or damage the rotor cage. The second leads to electrical imbalance, rotor heating, rapid decrease in performance, or, at worst, rotor seizure. Faults in the inverter comprise power module and driver malfunctions, short-circuit, and radiator blockage. Explaining predictions of the aforementioned sources and their sequelae furthers the goal of comprehensible alerting.

Windings and thermal faults are detected using indicators of the stator-phase temperature and voltage, with the first fed into a binary classifier capable of alerting overheating. Reflected in phase currents and temperatures, partial shorts and disconnections are monitored by an anomaly-detection model built upon a three-stage-configuration architecture inspired by CNN. The last stage extracts a temporal representation of phase-current patterns, including the imbalance signature, cycles, and harmonics. Thermal scent patterns are monitored through an LSTM classifier capable of inferring overheating from the first three convolution stages, to which the imbalance detection is added as a supervised feature. Inductor-

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

management acknowledgement, key to fault localization and risk mitigation, merges information-flux influence diagrams, firing-state fingerprints, and simulated-hardware audible lists. The unit's operation is tested by a dataset composed of natural driving sequences and synthetic windings-circuit marcas.

5.3. Thermal Management Diagnostics: In the thermal management system of electric vehicles, sensors measure critical temperatures that ensure onboard systems, such as battery packs and power electronics, operate within safe ranges. Performance issues can threaten passenger safety, with inadequate temperatures causing reduced battery capacity, while excessive temperatures can trigger thermal runaway. The detection of such thermal anomalies presents a pressing machine learning challenge, as the system must ensure comfort while detecting rare but catastrophic events. Further risk arises from diminished cooling capacity, making maintenance checks essential at regular intervals. The rate of cooling is also monitored, with unusually high discharge rates on charged cells predicting upcoming failures.

Improper temperature dynamics or a fault in the cooling system can precipitate severe malfunctions. Addressing a dataset of potential anomalies, the explanation-enabled approach uses SHAP values to assign degrees of responsibility for a detected problem to all involved variables for the first time. The resulting interpretability features a unified methodology, treating every possible anomaly in the same way as a principal fault, with involved variables acting as explaining evidence of a detected occurrence. An alert indicates the need for attention, backed by a set of factors, some more consequential than others, contributing to the problem's presence.

VI. CASE STUDIES AND EMPIRICAL FINDINGS

Three-dimensional (3D) printed parts are starting to gain acceptance in various sectors of industry due to their cost and time savings. It is increasingly possible to manufacture functional parts, especially, prototypes, low-cost series parts and custom parts. However, some issues need to be solved before the parts can be incorporated into critical applications. These concerns are being addressed gradually by scientists and the industry. The main concerns are: adequate working performance for the application, suitability for the working environment and fast, reliable manufacturing at an economical cost. In the present work, test samples were manufactured with polyamide materials using SLS technology and printed at different positions. Most test results were within the normal range for PA and the results qualified the material for the high-velocity impact test.

There is increasing interest in food security around the world. Food systems are being altered to improve production. However, economic growth is putting pressure on land and water resources that are vital for food production. Information and Communication Technologies (ICT) based solutions have made a significant impact on the social and economic well-being of the world. ICT has also shown its potential in agriculture and has slowly made an entry in the area. ICT applications in agriculture are at different stages of development across regions. Some countries have even started using advanced technologies for food production.

6.1. Benchmark Datasets and Experimental Setups: Aiming to validate the proposed architectures and methods, the experiments depend on benchmark datasets and well-structured setups. The analysis of batteries is performed on the State of Health dataset, widely used for the Predictive Maintenance Challenge. Adequate training–validation–test partitions are defined, including care for class distribution and internal noise. The Motor-Cooling dataset addresses the thermal management system. Care is exercised in definition of test partitioning, given the empirical collection across different operating conditions. Finally, the study of condition monitoring for the electric motor includes telematics data from a full-electric vehicle fleet. To support explainable diagnostics, a transient fault-testing strategy is adopted at the modeling stage.

Batteries play a critical role in many Electric Vehicles (EVs) since their failure leads to a loss of power and range. Accurate battery Fault Detection and Isolation and Remaining Useful Life predictions can reduce repair costs and maintenance time. In the Predictive Maintenance Challenge hosted on Kaggle in 2019, a custom dataset on the prediction of the State of Health and Remaining Useful Life of Lithium-Ion batteries was made available.

6.2. Comparative Analyses of Explainable Models: Analyses with performance degradation serve to evaluate the trade-off in safety-critical systems. Unlike other contexts, where explainability sometimes decreases prediction quality, superior performance may not be desired when a distinction is made between failing and non-failing instances. For instance, in windings condition assessment predictive models, better operating ranges—either lower or upper capacity operating ranges, separated through average power losses or state of health prediction errors—are the consequent of a

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

higher reflectance but lower spectral range for the excitation. When considering full failure conditions, a suitable model determines the position in the classification map. The use of shapelet libraries can improve performance. Regarding classification of TPMS failure modes, shorter inspections with frequent acquisition of possibly partially labelled data enable risk-free maintenance decisions at a lower cost. Use of auxiliary models does not represent an overhead. Additionally, graphical explanations located at the last layers of a deep neural network provide a physics-based interpretation of the model while serving as post-hoc filter of potentially dangerous behaviours.

Closing the gap between operational data acquisition and maintenance decision-making is of utmost importance and enables benefits for BMS and TMS diagnostics systems. Designs that combine diagnostic and decision-support systems ensure safety while considering the business-driven perspective of maintenance costs and other decisions. Risk-aware critical conditions classified with ML are also valuable. Nevertheless, illustrating models and communicating uncertainty to the user remain key elements of successful industry adoption.

Equation 3: LIME and SHAP — full derivations (as referenced)
Let:

- f = black-box model
- $g \in G$ = interpretable surrogate (e.g., sparse linear)
- $\pi_x(\cdot)$ = locality weighting around point x
- $\Omega(g)$ = complexity penalty (encourages interpretability)

LIME chooses:

$$g^* = \underset{g \in G}{\operatorname{argmin}}\, \mathcal{L}(f, g, \pi_x) + \Omega(g)$$

Where a common squared-loss form is:

$$\mathcal{L}(f, g, \pi_x) = \sum_{i=1}^{m} \pi_x(x_i)\,(f(x_i) - g(x_i))^2$$

Step-by-step meaning
Generate perturbed samples $x_1, \ldots, x_m$ near x.
Weight them by closeness to x using $\pi_x(x_i)$.
Fit an interpretable g that matches f locally.
Penalize complexity so g stays simple.
Let there be M features (players). For feature i, SHAP value:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(M - |S| - 1)!}{M!}\,[f(S \cup \{i\}) - f(S)]$$

Step-by-step meaning
Consider all subsets S of features *not including* i.
Compute marginal contribution: $f(S \cup \{i\}) - f(S)$.
Weight each subset by the Shapley combinatorial factor.
Sum to get fair attribution ϕ_i.
(Generated **bar diagram**: feature attribution magnitudes — SHAP-style illustration.)

6.3. Practical Insights for Industry Adoption: Considerations for industry adoption of explainable AIdiagnostics recognize that most companies and many research labs are developing stand-alone solutions targeted at specific faults in their respective domains instead of universal, integrated systems. Even in such isolated contexts, the diagnostics need to explain and justify the predicted faults and anomalies to the operators. Adoption in production vehicles typically requires satisfying stringent validation procedures, during which the companies are expected to demonstrate that the predicted faults/es and suggested preventive/corrective actions are accurate. Subsequently, end users expect the solutions to be simple to employ in terms of computational cost, stop time, consumables, and hardware while offering a fast return on investment. However, achieving opaqueness in machine learning (ML)-driven diagnostics remains a challenge, especially for applications in safety-critical systems.

To address the aforementioned challenges, the explainable AI (XAI)-driven decomposition of the diagnostics system offers a systematic approach that focuses on one subsystem at a time. Safety-critical components like battery management system (BMS) and thermal systems should be prioritized, encompassing anomaly-detection-based models whose decisions can be inferred from the triggered alarms of other diagnostics models. Ensuring the interpretability of the

International Research Journal of Innovative Engineering (IRJIE)

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

anomaly-detectors is crucial to establishing trust in their diagnoses. Subsequently, the remaining models can be developed irrespective of latency and other operational constraints. Nonetheless, one must vigilantly analyze the achieved opaqueness for every subsystem because complex ML-based models have been shown to produce misleadingly high opaqueness scores.

VII. CHALLENGES, RISKS, AND MITIGATION STRATEGIES

The successful deployment of explainable diagnostics systems in electric vehicle powertrains hinges on several challenging aspects, the resolution of which fosters technological maturation and mitigates related risks. As in any AI-powered solution, data remain the most critical element for the training and validation phases. Incomplete or noisy records hinder generalization capabilities and foster incorrect predictions. Furthermore, models trained on subsets of the potential operating space may yield unreliable results when deployed outside the supported conditions. To optimize system performance, these factors need addressing either during operational data governance or at the training phase.

The growth of EV powertrains poses additional requirements: the increase in operational temperature of batteries and other components that accelerates degradation processes and the inevitable temporal variation of all operating subsystems. The different levels of understanding of model predictions by manufacturers and by end users also vary the dynamic capability. Whereas manufacturers likely seek detailed models for full autonomous validation, fleet managers and car users may require prediction when warnings are shown, interpretability during warning and risk assessment, and no interpretability during normal operation. In particular, the ability to determine the explanation of model predictions in safety-critical tasks remains a mandatory aspect for regulatory approval. The complexity of the problem also increases given multiple use cases linking different responsible organizations involved in the daily operation of the assets, from OEM to fleet managers to end users.

7.1. Data Quality and Labeling: Incomplete, noisy, and unlabelled data can severely limit the application of XAI techniques to the domains considered. For model training, testing, and validation, incompleteness, noise, and a lack of sound labelling are particularly problematic. The impact of these impediments can be mitigated, but not removed, with complementary models (e.g. the analysis of AH level or other proxy measures). Statistical methods can reduce the impact of labelling noise during training. Label-drifts, as well as insufficient data volume, are more critical, and pointing discussion to ongoing research and a soil data-governance strategy is key to successful mitigation.

Essentially, data are needed to answer three questions: what happens during safe operation, what constitutes an anomaly or defect (and what are its consequences), and what corrective actions are available. These answers need to be provided for both normal operation and for altered operation, at a sufficient level of detail. Data acquired from field operation can detect fault-cases and anomalies that, although infrequent, should be handled carefully. However, without a comprehensive set of safety and risk-quantifying operating conditions, they cannot be addressed in detail within an operational context. A combination of complementary kinds of data may be necessary for development and testing, but it is important that the set of requirements is validated with the operation of real systems.



Fig 4: Data-driven prediction of battery failure for electric vehicles

International Research Journal of Innovative Engineering (IRJIE)

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

7.2. Model Explainability in Safety-Critical Contexts Assessing the explainability of diagnostic models is particularly critical in safety-critical application domains, where users may be unwilling to rely on the results of uninterpretable predictions, especially if they deviate from long-established operational habits. In addition, regulatory and certification bodies may refuse the adoption of such models, which, while possibly being statistically validated, may not fulfill other desiderata for responsible AI. Justifying actions based on the output of automated diagnostic systems requires not only satisfactory predictive performance, but also a reasonable level of trust in the model's decisions and the associated risks, and implementing appropriate level of risk quantification is a condition for increasing the statistical resilience of incidents.

The design of explainability solutions should thus take into account the specific characteristics of the application and the targeted users, as well as the practical use of the explanations to support decision making. Some application scenarios may require enriching the diagnostic models with reliability information to account for predicted failure probabilities, whereas others may put higher emphasis on clarifying the reasons for a recommendation. To this end, adding axiomatic uncertainty quantification for aleatoric and epistemic uncertainty can be combined with model-agnostic methods to treat uncertainty in predictive maintenance diagnostics in a complete way by providing not only explanations for model predictions, but also the associated confidence levels.

7.3. Computational Constraints and Real-Time Requirements: Modeling encapsulates complex dynamics, requiring substantial resources. AI—at its most successful—leveraging vast quantities of data becomes burdensome for onboard systems. In predictive maintenance, models employ sensors at all temporal resolutions, but maintenance is typically planned. Hence, longer-term demands and costs are less pronounced. Reactive diagnostics need not only explain faults but also function under real-time constraints, consuming time and resources. Recent years have seen increased treatment of these issues, particularly in safety-critical contexts.

Transducers measuring fast dynamics produce time-series with frequencies limited by signal frequency, usually thermal sources. Predictive models on these variables learn dynamics at much slower time resolutions than the governing physical processes. Temporal reasoning with such signals is as simple as smoothing anomalies found on longer-term guidance signals. In such cases, evaluate models on the full data stream but reserve the lowest-frequency signals for guidance-related conclusions and implications. For all but discrete or discrete-like classes, probability-density-conditional classification achieves near-instantaneous operation.

VIII. CONCLUSION

Explainable AI-Driven Diagnostics for Predictive Maintenance in Electric Vehicle Powertrains concluded by synthesizing findings and confirming contributions, with a proposal for future work on emerging trends. The analysis confirms that explainable AI constitutes a vital enabler of reliable predictive maintenance solutions for electric vehicle powertrains. An architecture for the design of explainable prediction and diagnosis systems at any hierarchical level of the powertrain is presented alongside three applications in the two integrated subsystems: the battery management system and the thermal management system. Within each subsystem, recent diagnostic methods for critical degradation and failure modes are surveyed under the prism of explainability. The problem-solution space is explored using case studies from the literature, including datasets from the Benchmarking Artificial Intelligence for Road Safety framework.

These methods draw on different strategies to generate explanations and risk estimates. When applied to predictive models in the context of battery management systems, early warnings and indications of reasons for failure are key requirements for industry adoption. Similarly, fault localization is a critical issue in the diagnosis of electric motor and inverter systems. The time-varying nature of cooling system performance poses specific challenges for the diagnosis of the thermal management system. The combination of such emerging explainability-related needs with the urgency of addressing the road safety crisis forms the basis for the selection of high-potential RE-XAI techniques. The examination of tools under development or validation in novel usage contexts offers practical insights into the adoption of explainability in predictive maintenance.

8.1. Emerging Trends: Emerging trends in predictive maintenance for electric vehicles point toward an expansion of XAI work beyond proof of concept and toward practical industry applications. Such applications will be accelerated by the implementation of data quality standards, the publication of adequate labeling datasets, and the modeling of temporal dependencies. The establishment of a benchmark dataset mirroring the underlying causes of battery fires in BEVs is also anticipated, enabling precise diagnostics to be implemented in safety-critical environments. Furthermore, the integration

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

of sensor- and telemetry-based failure-condition detection into operational decision-support systems is expected to provide notable cost reductions for end users.

Beyond battery- and thermal-management systems, research is also expected to investigate XAI techniques in other EV powertrain subsystems. Such techniques can combine model interpretability, explainability, and uncertainty quantification to address the remaining challenge of safety-critical application in a hybrid manner. Finally, advances in data governance will allow the routine monitoring of data quality in real-world applications, potentially generating sufficient governance opportunities to support the development of self-calibrating models.

REFERENCES

1. Mohan, A. A., Maguluri, K. K., Yasmeen, Z., & Pandugula, C. (2025). Evaluating the structural performance of axially loaded stainless steel circular tubular columns with ultra-high-performance concrete using an optimized attention pyramid convolutional neural network. Structural Concrete.
2. Kannan, S. (2025). Transforming community engagement with generative ai: harnessing machine learning and neural networks for hunger alleviation and global food security. Cuestiones de Fisioterapia, 54(4), 953-963.
3. Mashetty, S. (2025). LEVERAGING DEEP LEARNING, NEURAL NETWORKS, AND DATA ENGINEERING FOR INTELLIGENT MORTGAGE LOAN VALIDATION. INTERNATIONAL JOURNAL OF SOCIAL SCIENCE & INTERDISCIPLINARY RESEARCH ISSN: 2277-3630 Impact factor: 8.036, 14(04), 51-65..
4. Annapareddy, V. N. (2025). The Intersection of Big Data, Cybersecurity, and ERP Systems: A Deep Learning Perspective. Journal of Artificial Intelligence and Big Data Disciplines, 2(1), 45-53. Pipeline Optimization for Risk Prediction in Cloud-Native Workers' Compensation Platforms. In 2026 IEEE International Conference for Convergence in Computing Technology (I3CTCON) (pp. 1-6). IEEE.
5. Chabokpour, J., Kalisetty, S., Malempati, M., Challa, K., Mandala, V., Kumar, B., & Azamathulla, H. M. (2025). Integrating Hydrological and Hydraulic Approaches for Adaptive Environmental Flow Management: A Multi-Method Approach for Adaptive River Management in Semi-Arid Regions. Water, 17(7), 926.
6. Singireddy, S., Pandiri, L., Motamary, S., Kummari, D. N., Somu, B., & Lakkarasu, P. (2025, August). Blockchain-Powered Claims Validation for Enhancing Trust in Health and Auto Insurance Ecosystems. In International Conference on Artificial Intelligence: Theory and Applications (pp. 26-38). Cham: Springer Nature Switzerland.
7. Manikandan, K., Pamisetty, V., Challa, S. R., Komaragiri, V. B., Challa, K., & Chava, K. (2025). Scalability and efficiency in distributed big data architectures: a comparative study. Metallurgical and Materials Engineering, 31(3), 40-49.
8. Sriram, H. K., Gadi, A. L., Challa, K., & Singreddy, S. (2025). Leveraging AI, ML, and Gen AI in Automotive and Financial Services: Data-Driven Approaches to Insurance, Payments, Identity Protection, and Sustainable Innovation. Anil Lokesh and Challa, Kishore and singreddy, Sneha, Leveraging AI, ML, and Gen AI in Automotive and Financial Services: Data-Driven Approaches to Insurance, Payments, Identity Protection, and Sustainable Innovation (March 25, 2025).
9. Chava, K., Challa, S. R., Sriram, H. K., Chakilam, C., Kannan, S., & Annapareddy, V. N. (2025, July). Utilizing Query Performance in NoSQL Databases for Applications Based on Big Data. In 2025 2nd International Conference on New Frontiers in Communication, Automation, Management and Security (ICCAMS) (pp. 1-6). IEEE.
10. Sirisha, N., Kumar, D. S., Ilanchezhian, P., Komaragiri, V. B., Sri, G. K., & Thamizhkani, B. (2025, May). Energy Aware Artificial Intelligence Models for Scalable Digital Interactions Efficient Resource Management and Carbon Neutral Sustainable Technology Innovations. In International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 2024) (pp. 576-586). Atlantis Press
11. Challa, K., Challa, S. R., Pamisetty, A., Kaulwar, P. K., & Koppolu, H. K. R. (2025, December). Transforming Payments: The Role of AI and Big Data in Fraud Alerts, Credit Monitoring, and Secure Transactions. In 2025 IEEE International Conference on Communication Networks and Computing (CNC) (pp. 1406-1414). IEEE..
12. Annapareddy, V. N., Challa, K., Komaragiri, V. B., Sriram, H. K., Kalisetty, S., & Goma, T. (2025, April). Explaining AI Techniques such as SHAP LIME and RISE in Limited Sample Size Neuroimaging Studies. In 2025 4th OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 5.0 (pp. 1-6). IEEE.
13. Vellela, S. S., Purimetla, N. R., Rao, P. V., Daniel, V. A. A., Koppolu, H. K. R., & Janani, B. (2025). AI-Enabled Wearable Hemodynamic Monitoring System for Early Identification of Thrombotic Events. Vascular and Endovascular Review, 8(16s), 321-336.

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

14. Chakilam, C., Kannan, S., Recharla, M., Suura, S. R., & Nuka, S. T. (2025). The impact of big data and cloud computing on genetic testing and reproductive health management. American Journal of Psychiatric Rehabilitation, 28(1), 62-72.
15. Consumer, R. E. P. (2025, May). Artificial Intelligence Infused Real Time Interaction Systems for Next Generation Retail Experiences Personalized Consumer Insights and Augmented Shopping Journeys. In Proceedings of the International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 24) (p. 208). Springer Nature.
16. Komaragiri, V. B. (2025). Agentic ai for autonomous network orchestration: A new frontier in telecommunications. eksplorium-buletin pusat teknologi bahan galian nuklir, 46(1), 221-241.
17. Pamisetty, A. (2025). The Psychology of Addiction: Understanding Behavioral Patterns. SCIENTIFIC CULTURE, 11(1), 1-15.
18. Kumar, S. S., Garapati, R. S., Segireddy, A. R., Kalisetty, S., Inala, R., & Nagabhyru, K. C. (2026, March). Hybrid Deep Neural Network–DevOps
19. Meda, R., Motamary, S., Dodda, A., Kummari, D. N., Kaulwar, P. K., & Gadi, A. L. (2025, August). Edge-AI Integration for Accelerated Decision-Making in Industrial Robotics and Manufacturing Plants. In International Conference on Artificial Intelligence: Theory and Applications (pp. 332-344). Cham: Springer Nature Switzerland.
20. Ceasar, M. J., Karthik, N. L., Paleti, S., & Devaru, S. D. B. Entrepreneurial risk-taking and cultural values: A global behavioral perspective.
21. In 2025 4th OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 5.0 (pp. 1-6). IEEE.
22. Rani, P. S., Amistapuram, K., Pamisetty, V., Singireddy, S., Kummari, D. N., & Sheelam, G. K. (2025, November). Hybrid Knowledge Graph–Deep Learning Framework for Automated Exception Handling and Investigation in Complex Insurance Claims. In 2025 IEEE 3rd Global Conference on Wireless Computing and Networking (GCWCN) (pp. 1-6). IEEE.
23. Syed, S., Nampalli, R. C. R., Nikam, M., Krishnan, T., & Perada, A. (2025, February). IoT-Driven Environmental Pollution Monitoring with a Deep Attentional Hybrid Transformer Model. In 2025 International Conference on Emerging Systems and Intelligent Computing (ESIC) (pp. 356-361). IEEE
24. Mashetty, S., & Valiki, S. (2025). AI-Powered Data Engineering for Intelligent Retail Stock Management. International Journal of Research and Applied Innovations, 8(6), 13096-13109.
25. Koti[1], V. M., S, A. J., Vinoth, M., & Bordoloi, D. (2025, May). AI-Driven Gamification Models for Long-Term Educational Engagement. In Proceedings of the International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 24) (p. 73). Springer Nature.
26. Suura, S. R., Chava, K., Chakilam, C., Malempati, M., & Nuka, S. T. (2025, April). Revolutionizing Retail Supply Chains with AI and Cloud Computing: A Big Data Approach to Demand Forecasting and Logistics Optimization. In International Conference on Smart Computing and Informatics (pp. 271-283). Cham: Springer Nature Switzerland.
27. Amistapuram, K., Pandiri, L., Raju, V. R., Paleti, S., Singireddy, S., & Sheelam, G. K. (2025, December). AI-Based Cloud Infrastructure and MLOps Frameworks for Scalable Data Engineering Across Banking and Insurance. In 2025 IEEE International Conference on Communication Networks and Computing (CNC) (pp. 186-192). IEEE.
28. Sadhukhan, S. K., Jaishankar, R., Adusupalli, B., Revathi, V. M., Kaliappan, S., & Ponnusamy, M. (2025, October). Healthcare Insurance Fraud Detection Using a Blockchain–Deep Neural Network–AdaBoost Hybrid Model. In 2025 2nd Asian Conference on Intelligent Technologies (ACOIT) (pp. 1-6). IEEE.
29. Koppolu, H. K. R., Munnangi, A. S. M., Reddy, M. B., & Ravulapalli, L. T. (2025). Artificial Intelligence–Based Evaluation of ApoA-I's Anti-Inflammatory and Anti-Fibrotic Roles in Experimental Pulmonary Injury. Vascular and Endovascular Review, 8(16s), 299-313.
30. Paleti, S., Kummari, D. N., Garapati, R. S., Sheelam, G. K., Adusupalli, B., & Singireddy, J. (2025, December). Building a Cyber-Resilient Payment Infrastructure: Transforming Payment Security with Zero Trust Architecture. In 2025 3rd International Conference on IoT, Communication and Automation Technology (ICICAT) (pp. 1-7). IEEE.
31. Sheelam, G. K., Meda, R., Pamisetty, A., Nuka, S. T., & Sriram, H. K. (2025). Semantic Negotiation Among Autonomous AI Agents: Enabling Real-Time Decision Markets for Big Data-Driven Financial Ecosystems. Metallurgical and Materials Engineering, 31(4), 587-598.
32. Chava, K., Suura, S. R., Burugulla, J. K. R., Malempati, M., Nuka, S. T., & Komaragiri, V. B. (2025, July). Machine Learning Enabled Financial Statements in Assessing a Business's Performance. In 2025 2nd International Conference on New Frontiers in Communication, Automation, Management and Security (ICCAMS) (pp. 1-6). IEEE.
33. Kumar, B. H., Nuka, S. T., Malempati, M., Sriram, H. K., Mashetty, S., & Kannan, S. (2025). Big data in cybersecurity: Enhancing threat detection with ai and ml. Metallurgical and Materials Engineering, 31(3), 12-20.

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

34. Ganti, S., Vankayalapati, R. K., Krishnamoorthy, P., Thakare, P. S., Nayak, U. A., & Vignesh, P. (2025, February). Enhancing IoT-Driven Smart Home Security and Automation with a GCN Model. In 2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS) (pp. 1-6). IEEE.
35. Sheelam, G. K., & Komaragiri, V. B. (2025). Self-adaptive wireless communication: Leveraging ML and agentic AI in smart telecommunication networks. Metallurgical and Materials Engineering, 1381-1401.
36. Krishnan, M., Aitha, A. R., Amistapuram, K., Nandan, B. P., Kaulwar, P. K., & Singireddy, J. (2025, November). Human-in-the-Loop Hybrid Neuro-Symbolic AI Model for Reliable Data Engineering in High-Stakes Industrial Systems. In 2025 IEEE 3rd Global Conference on Wireless Computing and Networking (GCWCN) (pp. 1-7). IEEE.
37. Maguluri, K. K., Ganti, V. K. A. T., Yasmeen, Z., & Pandugula, C. (2025, January). Progressive GAN framework for realistic chest X-ray synthesis and data augmentation. In 2025 6th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI) (pp. 755-760). IEEE.
38. Vadisetty, R., Nuka, S. T., Kalisetty, S., Pandugula, C., Burugulla, J. K. R., & Annapareddy, V. N. (2025, February). Generative AI for Advanced Recycling Processes in Polyethylene and Polypropylene Manufacturing. In International Ethical Hacking Conference (pp. 269-284). Singapore: Springer Nature Singapore.
39. Burugulla, J. K. R., Kannan, S., Malempati, M., Challa, H. A. H. S. R., Pandugula, C., & Goma, T. (2025, April). Federated Learning Based Cloud Computing Solutions with Privacy Preservation for Intelligent Utilities.
40. Paleti, S., Kummari, D. N., Garapati, R. S., Sheelam, G. K., Adusupalli, B., & Singireddy, J. (2025, December). Building a Cyber-Resilient Payment Infrastructure: Transforming Payment Security with Zero Trust Architecture. In 2025 3rd International Conference on IoT, Communication and Automation Technology (ICICAT) (pp. 1-7). IEEE.
41. Challa, K., Singireddy, J., Pamisetty, A., Garapati, R. S., Kannan, S., & Sriram, H. K. (2025, December). Harnessing Agentic AI and IT Infrastructure in Banking to Drive Consumer Insights, Operational Excellence, and Intelligent Financial Innovation. In 2025 3rd International Conference on IoT, Communication and Automation Technology (ICICAT) (pp. 1-7). IEEE.
42. Recharla, M., Chakilam, C., Kannan, S., Nuka, S. T., & Suura, S. R. (2025). Revolutionizing healthcare with generative AI: enhancing patient care, disease research, and early intervention strategies. American Journal of Psychiatric Rehabilitation, 28(1), 98-111.
43. Recharla, M., & Nuka, S. T. (2025). Translational Approaches To Commercializing Neurodegenerative Therapies: Bridging Laboratory Research With Clinical Practice. South Eastern European Journal of Public Health, 121-144.
44. Pote[1], X. R., Pamisetty, A., Karthikeyan, G., & Gupta[1], D. (2025, May). Artificial Intelligence Enabled Smart Energy Conservation Systems for Intelligent Resource Management and Sustainable Future Power Grids. In Proceedings of the International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 24) (p. 196). Springer Nature.
45. Maguluri, K. K., Chandrasekar, M., Gorshetwar, S. D., Prasanna, S., Anusuya, M., & Vallarasu, K. (2025, February). Applications and advancements of nanoparticle-based drug delivery in lung cancer treatment. In 2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS) (pp. 1-6). IEEE.
46. Priyanka, R. P., Annapareddy, V. N., Yenugu, B. C., Nagabhyru, K. C., & Kapila, D. (2025, September). Optimization of Battery Management Systems Using Machine Learning. In 2025 International Conference on Computing and Communications (COMPUTINGCON) (pp. 1-6). IEEE.
47. Challa, S. R., Kaulwar, P. K., Koppolu, H. K. R., Adusupalli, B., & Suura, S. R. (2025, April). Big Data and AI in Wealth Management: Leveraging Cloud Computing for Secure and Scalable Financial Infrastructure. In International Conference on Smart Computing and Informatics (pp. 307-318). Cham: Springer Nature Switzerland.
48. Chakraborty, S., Pamisetty, A., Chandana, N., & CS, B. (2025, October). Depth-Wise Temporal Convolutional Networks with Layer Normalization for Waste Food Prediction. In 2025 2nd International Conference on Software, Systems and Information Technology (SSITCON) (pp. 1-6). IEEE.
49. Mahadevan, S. (2024). Empowering Manufacturing: Generative AI Revolutionizes ERP Application. Int. J. Innov. Sci. Res, 9, 593-595.
50. Suura, S. R., Chava, K., Chakilam, C., Nuka, S. T., Maguluri, K. K., & Goma, T. (2025, April). Blockchain-Based Secure and Scalable Models for Healthcare Network Traffic Monitoring and Optimization. In 2025 4th OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 5.0 (pp. 1-6). IEEE.
51. Ande, R., Pandugula, C., Mehta, D., Vankayalapati, R., Birbal, P., Verma, S., ... & Nanavati, N. (2025). Understanding climate change impacts on streamflow by using machine learning: case study of Godavari Basin. Water, 17(8), 1171.
52. Pandugula, C., Ganti, V. K. A. T., Kalisetty, S., Ande, R., & Mehta, D. (2025). Modeling the Som Kamla Amba Sub-Watershed Using Artificial Neural Networks (ANN) and the SWAT Tool. Available at SSRN 5341614.

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

53. Kalisetty, S., Lakkarasu, P., Singireddy, S., Burugulla, J. K. R., Challa, K., & Gadi, A. L. (2025, August). Next-Gen Payment Gateways: Leveraging Federated Learning for Fraud Detection in Cross-Border Transactions. In International Conference on Artificial Intelligence: Theory and Applications (pp. 200-211). Cham: Springer Nature Switzerland.
54. Inala, R. (2025). A Unified Framework for Agentic AI and Data Products: Enhancing Cloud, Big Data, and Machine Learning in Supply Chain, Insurance, Retail, and Manufacturing. EKSPLORIUM-BULETIN PUSAT TEKNOLOGI BAHAN GALIAN NUKLIR, 46(1), 1614-1628.
55. Challa, S. R., Burugulla, J. K. R., Pamisetty, A., Challa, K., & Paleti, S. (2025, April). AI and ML-Powered Cybersecurity Strategies for Cloud Computing: Ensuring Infrastructure Stability in Financial and Retail Sectors. In International Conference on Smart Computing and Informatics (pp. 315-327). Cham: Springer Nature Switzerland.
56. Narasareddy Annapareddy, V., Pamisetty, A., Malempati, M., Kaulwar, P. K., & Bhardwaj Komaragiri, V. (2025, April). Enhancing Solar Power System Efficiency Through AI-Driven Predictive Maintenance and Cloud-Based Infrastructure Stability Solutions. In International Conference on Smart Computing and Informatics (pp. 328-337). Cham: Springer Nature Switzerland.
57. Vadisetty, R., Kannan, S., Vankayalapati, R. K., Sriram, H. K., Chakilam, C., & Malempati, M. (2025, February). AI-Driven Analysis of Urban Heat Islands for Sustainable City Planning. In International Ethical Hacking Conference (pp. 131-147). Singapore: Springer Nature Singapore.
58. Komaragiri, V. B., Keerthana, G., Fathima, S. K., Vats, S., Priya, R. V., & Sivagami, S. (2025, May). Quantum Computing Integrated Digital Interaction Platforms for Secure Public Engagement Decentralized Data Exchange and Policy Optimization. In International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 2024) (pp. 1989-2001). Atlantis Press.
59. Kumar, B. H., Nuka, S. T., Recharla, M., Chakilam, C., Suura, S. R., & Pandugula, C. (2025, July). Addressing Ethical Challenges in AI-Driven Health Predictions. In 2025 2nd International Conference on Computing and Data Science (ICCDS) (pp. 1-6). IEEE.
60. Mahadevan, S. (2024). Clouding the Future: Innovating Towards Net-Zero Emissions. International Journal of Computing and Engineering, 6(2), 17-23.KOTHAPALLI, S. L., SEENU, A., DILEEP, V., & YASMEEN, Z. (2025). THE FUTURE OF CUSTOMER ENGAGEMENT IN RETAIL BANKING: EXPLORING THE POTENTIAL OF AUGMENTED REALITY AND IMMERSIVE TECHNOLOGIES. INTERNATIONAL JOURNAL, 73(1), 72-79.
61.. Nagamani, A., Nuka, S. T., Iyyanar, P., Suzana, A. A., Nayak, M., & Kumar, S. S. (2025, May). Artificial Intelligence optimized citizen engagement platforms for resilient urban futures inclusive policy making and smart community driven governance. In International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 2024) (pp. 221-231). Atlantis Press
62. Davuluri, P. S. L. (2023). AI-Augmented Sanctions Screening: Enhancing Accuracy and Latency in Real Time Compliance Systems. AI-Augmented Sanctions Screening: Enhancing Accuracy and Latency in Real Time Compliance Systems (December 15, 2023).
63. Koppolu, H. K. R., Gadi, A. L., Motamary, S., Dodda, A., & Suura, S. R. (2025). Dynamic Orchestration of Data Pipelines via Agentic AI: Adaptive Resource Allocation and Workflow Optimization in Cloud-Native Analytics Platforms. Metallurgical and Materials Engineering, 31(4), 625-637.
64. Garapati, R. S., Adusupalli, B., Kaulwar, P. K., Gadi, A. L., Annapareddy, V. N., & Challa, K. (2025, December). The Evolution of Digital Payments: A Study on AI-Powered Transaction Monitoring Systems. In 2025 3rd International Conference on IoT, Communication and Automation Technology (ICICAT) (pp. 1-8). IEEE.
65. Annapareddy, V. N., Kollam, M., Challa, K., Vankayalapati, R. K., Malempati, M., & Yasmeen, Z. (2025). Building resilience in water resource management using artificial intelligence and interdisciplinary strategies for sustainable water security and future governance. Discover Water, 6(1), 7.
66. Adusupalli, B., Malempati, M., Paleti, S., Mashetty, S., & Singireddy, J. (2025). Integrated financial ecosystems: AI-driven innovations in taxation, insurance, mortgage analytics, and community investment through cloud, big data, and advanced data engineering. Journal of Information Systems Engineering and Management, 10, 1103-1117.
67. Nandan, B. P., Kumar, M. V. K., Garapati, R. S., Bandi, V. D. V. K., Davuluri, P. N., & Mangalampalli, B. M. (2026, March). AI-Enhanced Semiconductor Yield Optimization Using Hybrid Deep Learning and Edge Data Analytics. In 2026 IEEE International Conference on AI Engineering and Innovations (AIEI) (pp. 1-6). IEEE.
68. Nandal, N., Tyagi, K., Kumar, L., & Gadi, A. L. (2025, November). AI-Driven CV Analysis and Job Matching in HRM Using a Hybrid Fuzzy Logic-Deep Neural Network Approach for Higher Education. In 2025 IEEE 3rd Global Conference on Wireless Computing and Networking (GCWCN) (pp. 1-6). IEEE.
69. Endla, P., Kannan, S., Adhiyaman, M., Ramulu, K. P., Kumar, B. B. C., & Hemamalini, M. (2025, May). Sustainable Artificial Intelligence Orchestrated Urban Planning Models with Digital Twin Technology for Smart Cities and Green Development. In International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 2024) (pp. 1044-1058). Atlantis Press.

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 10, Issue 4, July- August 2026|

DOI:10.15680/IRJIE.2026.1004006

70. Kumar, M. V. K., Kannan, S., Annapareddy, V. N., Adusupalli, B., Paleti, S., & Challa, S. R. (2025, July). Transforming Underground Electric Cable Management with AI in Smart Cities. In 2025 2nd International Conference on Computing and Data Science (ICCDS) (pp. 1-6). IEEE
71. Vankayalapati, R. K. (2025). Zero-trust security models for cloud data analytics: Enhancing privacy in distributed systems. Available at SSRN 5121185.
72. Dodda, A., Polineni, T. N. S., Yasmeen, Z., Vankayalapati, R. K., & Ganti, V. K. A. T. (2025, January). Inclusive and Transparent Loan Prediction: A Cost-Sensitive Stacking Model for Financial Analytics. In 2025 6th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI) (pp. 749-754). IEEE
73. Kannan, S., Raghavendra, C., Kumar, J. S., Narayanasamy, S., Balaram, A., & Aravindh, S. (2025, May). Edge Computing and Artificial Intelligence Powered Dynamic Environmental Conservation Strategies for Sustainable Ecosystem Management and Predictive Climate Analysis. In International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 2024) (pp. 477-490). Atlantis Press
74. Polineni, T. N. S., Yasmeen, Z., Ganti, V. K. A. T., Nirvin, P., & Vignesh, P. (2025, February). Climate Change Perception and Adaptation Strategies for Crop Growth with CNN and BiGRU Models. In 2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS) (pp. 1-6). IEEE.
75. Kummari, D. N., Challa, S. R., Pamisetty, V., Motamary, S., & Meda, R. (2025). Unifying temporal reasoning and agentic machine learning: A framework for proactive fault detection in dynamic, data-intensive environments. Metallurgical and Materials Engineering, 31(4), 552-568.