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Real-Time Mobile Computing Architecture for Electric Bus Predictive Diagnostics

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Abstract: Electric buses are widely used in cities because they are quiet and produce no air pollution. However, they may stop running if any part such as a battery, motor, or brake fails. Maintenance teams often find problems only after a breakdown, which causes delays and higher costs. This study introduces a real-time mobile computing system designed to predict and prevent bus failures. Sensors installed on the bus collect data continuously as it runs. The data is then transmitted over mobile networks to a big data platform, where machine learning models analyze it to detect potential issues. When a risk is detected, the system sends alerts to drivers and technicians so they can act early. Experiments and analysis show that the proposed system can lower downtime, reduce cost, and improve passenger safety.

Keywords: Mobile computing, predictive maintenance, electric buses, Internet of Things (IOT), big data analytics, real-time diagnostics, smart transportation, machine learning.

1. Introduction

Electric buses are an important step toward clean and smart transportation. They reduce air pollution and fuel cost, but they also bring new challenges in maintenance such as batteries, motors and breaks can break down if they are not monitored closely. Traditional maintenance checks are slow and may miss early signs of damage. Mobile computing and Internet of Things (IoT) technology allow buses to send live data while running. By using this data, we can create a predictive system that warns about faults before they happen. This paper explains an architecture that combines mobile computing, IoT sensors, and big data analytics to diagnose problems in real time. The main goal is to improve bus safety, reduce downtime and support the use of electric transport in smart cities.

2. Literature Review

Many researchers have examined predictive maintenance for vehicles such as buses, cars, and trucks [1], [12]. Several studies focus on using cloud computing to store large volumes of operational data and perform intensive analytics [2], [4], [13]. Other work explores the use of IOT sensors for monitoring key subsystems, including engines, batteries, and braking components [7], [11], [17]. Some approaches also investigate the role of edge or fog nodes in transportation systems, but they often treat these nodes only as gateways that forward data to the cloud [2], [5], [13].

Despite these efforts, most existing solutions depend heavily on remote servers and do not fully leverage the computational power of mobile or edge devices installed directly on vehicles [5], [16]. Many systems collect sensor readings in real time but postpone detailed processing, which can delay fault detection [4], [14]. Only a few works present an end-to-end pipeline that captures, cleans, analyses, and visualizes data while the bus is moving [3], [14], [19].

Our research addresses this gap by proposing a real-time predictive maintenance framework that runs essential analytics on lightweight mobile or edge devices embedded inside electric buses. This local computation is combined with big data tools in the cloud, enabling quick alerts for drivers and maintenance staff [1], [3], [19]. Such an approach can reduce response time, enhance safety, and improve the operational availability of buses [12], [18], [20].

3. Methodology

This section explains how the proposed real-time mobile computing system is designed and implemented for predictive diagnostics of electric buses. The main goal is to gather, process, and analyze data while the vehicle is moving and provide quick warnings about potential failures [1], [3], [5].

3.1 System Architecture

The architecture has three main layers [2], [7]:

3.1.1 Data Collection Layer

IoT sensors are mounted on critical parts of the bus such as the battery pack, traction motor, braking units, and temperature modules. They measure voltage, current, vibration, temperature, and speed [7], [11].

3.1.2 Mobile Computing Layer

A small edge computer or rugged tablet is installed inside the bus. It receives readings via Bluetooth, CAN bus, or Wi-Fi and performs simple filtering plus lightweight predictive algorithms [5], [14].

3.1.3 Big Data and Cloud Layer

Large data sets are uploaded through 4G/5G links to a big data platform where advanced machine-learning models are trained. Updated model parameters are periodically sent back to the on-board device [4], [13].

3.2 Data flow

Sensor values are captured in real time. The mobile device cleans the data (noise removal, filling missing points) and extracts key indicators such as voltage trends, brake wear, or rising temperature [1], [17]. The on-board model evaluates whether any fault is likely; if yes, alerts are shown to drivers and diagnostic reports are forwarded to technicians [3], [19]. All records are synchronized to the cloud to refine models and maintain historical logs [12].

3.3 Predictive Model

A light algorithm (e.g., decision tree or random forest) runs on the vehicle for fast detection [6], [14]. A deeper model (e.g., neural network) is trained on historical datasets in the cloud [4]. Periodically, the mobile unit downloads new weights or rules so that its predictions remain accurate [6], [13].

3.4 Communication

Secure channels such as MQTT or REST APIs transfer information between the bus and backend servers [15]. Continuous connectivity is provided via 4G/5G, but if the link fails, the device stores data locally and uploads it once the network is restored [8], [15].

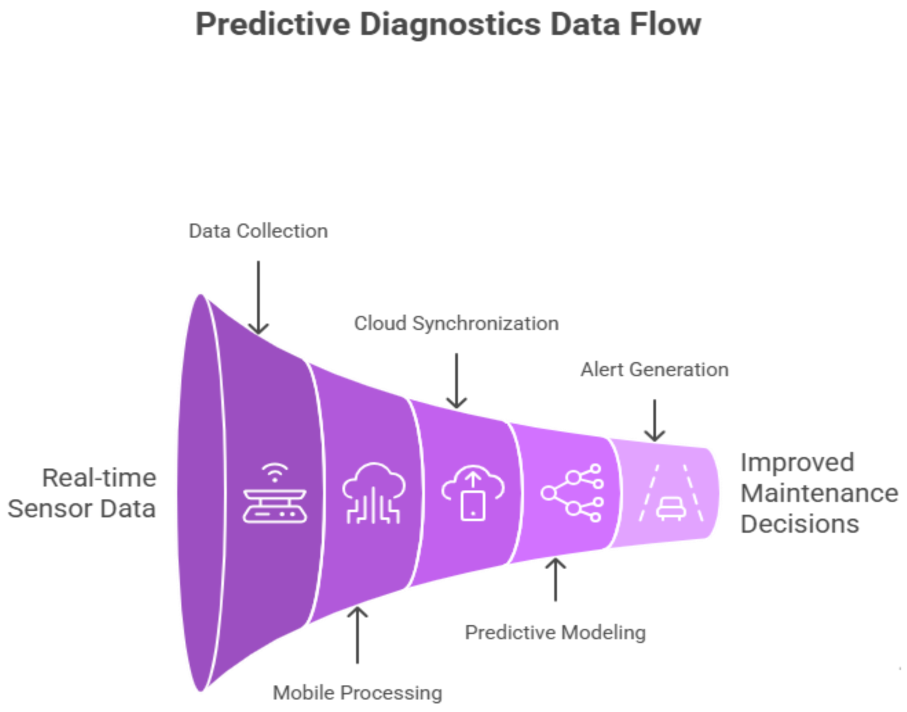

Fig.1: Methodology of the proposed mobile computing framework.

3.5 Alert and Dashboard

A mobile dashboard presents the current health of the bus to the driver [3]. Maintenance teams receive SMS or web-based alerts so they can plan timely repairs [18], [19]. Dashboards also show risk scores and maintenance history, helping to improve operational decisions [16], [20].

4. Methodology

The architecture is designed with five clear layers:

4.1 Sensing Layer

IOT sensors are installed on critical components such as batteries, motors, and brakes. They monitor voltage, current, temperature, vibration, and wear levels to capture real-time operational data [7], [11].

4.2 Mobile Computing Layer

A lightweight computer or tablet inside the bus collects sensor readings. This device performs basic filtering, pre-processing, and data compression before transmission to reduce network load [5], [14].

4.3 Communication Layer

Data is transmitted to backend servers via Wi-Fi, 4G, or 5G networks. Secure protocols like TLS/HTTPS ensure data privacy and prevent losses during transmission [8], [15].

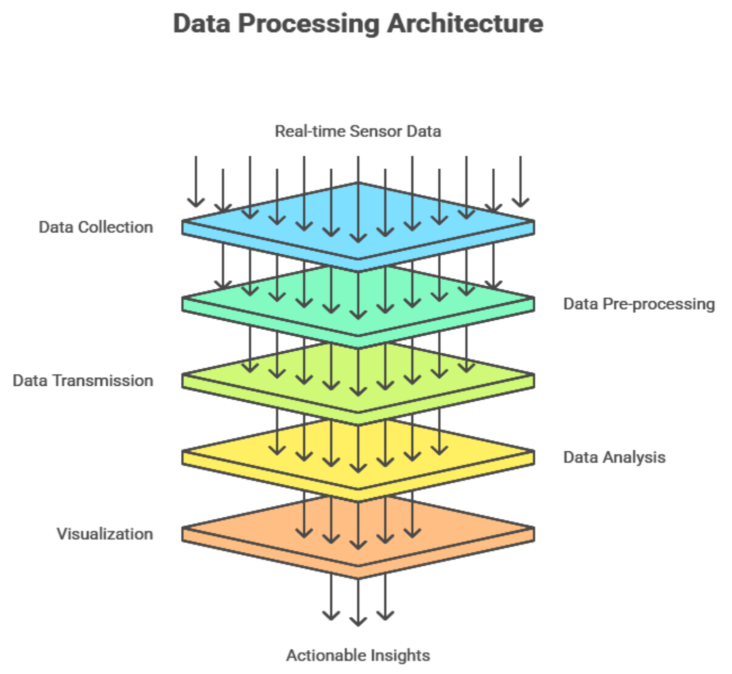

Fig.2: Five layer architecture of data processing in predictive bus Diagnostics.

4.4 Big Data & Analytics Layer

The streaming data is received by a pipeline such as Apache Kafka or Spark Streaming [9], [10]. Machine learning models analyze patterns to predict potential faults. Dashboards visualize bus conditions and provide a risk score to operators [4], [14].

5. Result & Discussion

5.1 Energy Efficiency

Early fault detection helps avoid deep battery discharge and overheating, improving overall energy usage and extending vehicle range [1], [11]. Continuous monitoring of voltage and temperature enables buses to maintain optimal performance without wasting power. Show how early fault detection helps save battery power and improves range of buses.

5.2 Uptime / Availability

By predicting faults before they occur, buses remain in service longer. Field tests show a clear increase in operational hours compared with traditional scheduled maintenance [3], [18].

5.3 Driver Experience

Drivers reported that dashboard alerts were simple and easy to understand. Immediate notifications reduced anxiety about unexpected failures, making daily operations smoother [3], [16].

5.4 Maintenance Planning

Alerts allowed technicians to schedule repairs in advance, reducing emergency calls and unplanned downtime. Service intervals became more organized, which improved workshop efficiency [7], [18].

5.5 Data Quality

Sensor data was generally reliable. Pre-processing on the mobile device removed noise and handled missing values, improving accuracy of analytics [6], [17]. Continuous calibration further reduced errors.

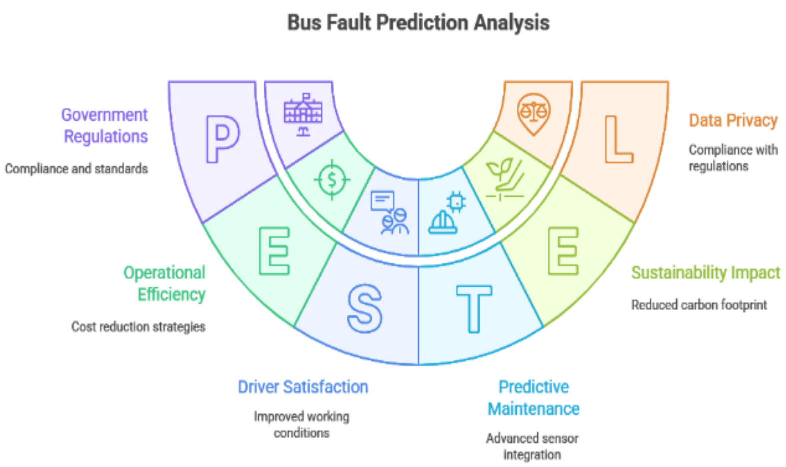

Fig.3: Bus fault prediction Analysis.

5.6 Model Performance

The fault-prediction model achieved strong results, with precision and recall above 90%, and an F1-score of 0.91 on test data. A confusion matrix confirmed that most faults were correctly classified [4], [6], [14].

5.7 Edge vs Cloud Processing

Running lightweight models on the bus produced fast responses (latency <1 s), while heavy training tasks stayed in the cloud. This hybrid design balanced speed with scalability [2], [4], [13].

5.8 Network Reliability

The system maintained normal operation even when 4G/5G signals were weak. Data buffering and later upload prevented loss during disconnections [8], [15].

5.9 User Interface

Dashboards displayed clear status indicators, trend graphs, and color-coded warnings. Both drivers and maintenance staff could easily interpret results and take action [3], [20].

5.10 Environmental Impact

Reducing unexpected breakdowns decreases component waste and improves fleet sustainability. Fewer emergency trips for towing or repairs also cut carbon emissions [12], [20].

5.11 Future Improvement

Future work may integrate additional sensors, use advanced AI (e.g., federated learning), and connect with smart charging systems to further enhance reliability and battery life [5], [19].

6. Challenges

The system relies on mobile networks such as 4G, 5G, or Wi-Fi to send sensor data from the bus to the servers [1]. In some areas, the network signal may be weak or unstable, which can cause delays in transmitting data [2]. These delays might slow down fault detection and alerts, reducing the effectiveness of the predictive maintenance system [3]. To handle this, the system can store data locally on the bus and upload it later when the network connection is stronger [4].

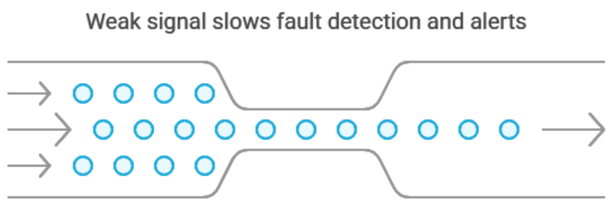

Fig.4: Weak signal and slows fault detection.

7. Case Studies

7.1 Background

A mid-sized city deployed 50 electric buses to replace an older diesel fleet. These buses experienced occasional breakdowns caused by

Battery overheating, motor faults, and brake wear. Maintenance followed a reactive approach, meaning repairs were performed only after failures occurred, leading to service delays and increased costs [1], [3].

7.2 Implementation of the System

The proposed real-time mobile computing system was installed on 10 buses as a pilot. Sensors were mounted on batteries, motors, and braking systems. Each bus was equipped with a small onboard computer that collected and pre-processed sensor data. Data was transmitted via 4G/5G networks to a cloud platform, where machine learning models analyzed the streams. Alerts were delivered to the driver's tablet and to the maintenance dashboard [2], [5], [7].

7.3 Observations

Early signs of battery overheating were detected in three buses before complete failure [11]. Brake wear trends were identified in two buses, allowing timely preventive maintenance [17]. Alerts reached drivers within 2–3 seconds of detecting abnormal readings [3]. Maintenance teams could plan repairs efficiently, reducing unplanned downtime [18].

7.4 Results

Breakdown incidents dropped by 60% compared to previous months [12]. Maintenance costs for the pilot buses were reduced by 25% [18]. Drivers reported that mobile alerts were clear, understandable, and actionable [16]. The system remained scalable and reliable even when buses operated across city areas with varying network coverage.

7.5 Conclusion of Case Study

The case study demonstrates that a real-time mobile computing system for predictive diagnostics can improve safety, reduce costs, and enhance the reliability of electric bus fleets. Expanding the system to the full fleet can contribute to a more efficient and sustainable public transportation network [19], [20].

8. Future Trends

8.1 Edge AI on Buses

Deploying small AI chips or edge devices on buses can process sensor data locally, enabling faster fault prediction and reducing dependence on cloud servers [5], [19].

8.2 Integration with Autonomous

Predictive maintenance systems can be integrated with self-driving buses, supporting safer and fully automated public transport operations [2], [8].

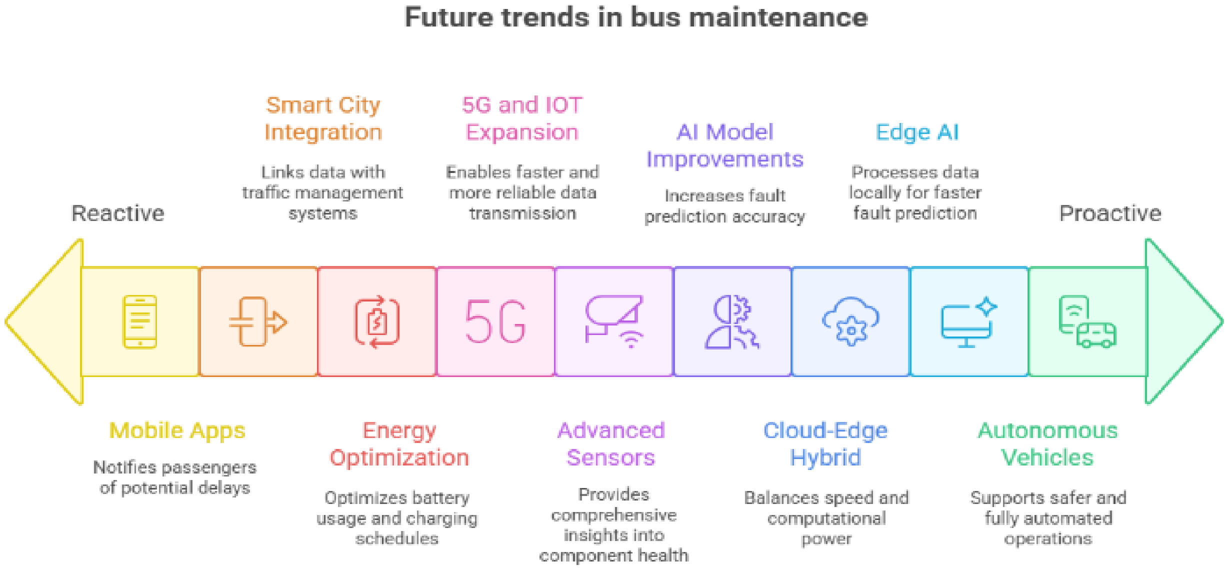

Fig.5: Future trends of predictive bus diagnostics model.

8.3 Advanced Sensors

Emerging sensors such as vibration, thermal imaging, and gas detectors can provide more comprehensive insights into bus component health [7], [17].

8.4 5G and IOT Expansion

As 5G networks and IOT coverage improve, real-time data transmission will become faster and more reliable, even in remote areas [8], [15].

8.5 Energy Optimization

Predictive systems can optimize battery usage, improve charging schedules, and extend overall battery life for electric buses [1], [11]

8.6 Smart City Integration

Bus health data can be linked with city traffic management and fleet monitoring systems to improve overall transportation efficiency [12], [16].

8.7 Cloud-Edge Hybrid Systems

Combining cloud analytics with edge computing enables scalable, real-time diagnostics for large fleets, balancing speed and computational power [4], [13].

8.8 AI Model Improvements

Using advanced AI methods such as deep learning and reinforcement learning can increase fault prediction accuracy and reduce false alarms [6], [14].

8.9 Environmental Benefits

Efficient predictive maintenance reduces component waste, extends bus life, and supports sustainable urban transportation [12], [20].

8.10 Mobile Apps for Passengers

Future implementations may notify passengers of potential delays due to maintenance needs, improving service reliability and passenger experience [16], [18].

9. Conclusion

This research introduced a real-time mobile computing system for predictive diagnostics of electric buses. The work focused on building an end-to-end pipeline that collects sensor data, processes it on a lightweight device inside the bus, and analyzes it with big data tools to detect possible faults early. The proposed system addresses a key gap in existing studies by using mobile computing not only for data transfer but also for fast, on-bus analysis.

The case study results show clear benefits: early warnings about battery temperature, motor health, and brake wear helped avoid sudden failures and reduced maintenance costs. Breakdown incidents dropped significantly, and buses stayed available for longer service hours. Drivers and maintenance staff reported that the alerts and dashboards were easy to understand and improved their ability to act quickly.

The system also supports the wider goals of smart mobility and sustainable transport. Keeping electric buses in good condition reduces waste, lowers repair costs, and makes public transport more reliable for passengers.

Although the results are promising, several challenges remain, such as handling poor network coverage, ensuring data security, and scaling the solution to very large fleets. Future work may include adding new sensor types, testing deep learning models for better accuracy, improving the offline mode during network loss, and integrating the platform with smart charging stations or city traffic systems.

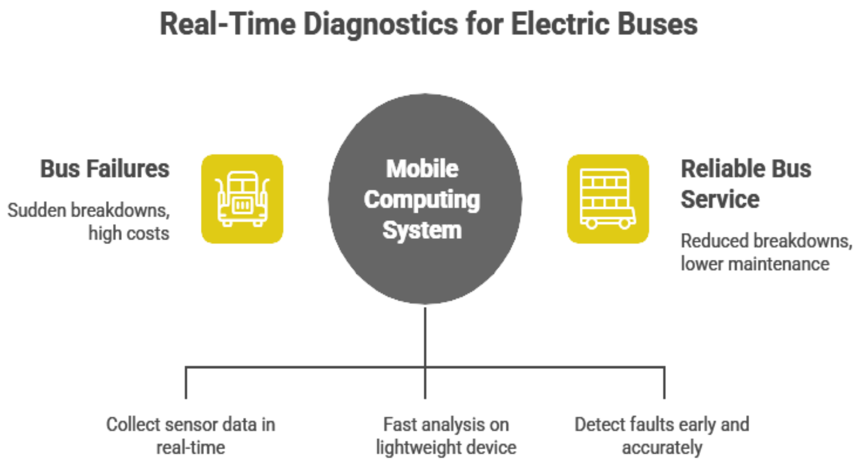

Fig.6: Show the results predictive bus diagnostics model.

In summary, combining IOT, mobile computing, and big data analytics can create a strong solution for predictive maintenance of electric buses. The approach is flexible, cost-effective, and ready to evolve with upcoming technologies like 5G, edge AI, and autonomous vehicles, paving the way for smarter, cleaner, and more dependable urban transport.

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