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Applying Industrial AI for Proactive Quality Control of ECUs in Automotive Production

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Abstract:
Electronic Control Units (ECUs) are the backbone of critical automotive subsystems, including engine management, braking, safety, infotainment, and advanced driver assistance systems (ADAS). As vehicles become increasingly software-defined and electronically controlled, the reliability of ECUs during manufacturing becomes paramount. Traditional quality control methods, while effective to an extent, often rely on rule-based testing and post-failure analysis, which can miss subtle defect patterns and lead to costly field failures, warranty claims, or recalls.This paper proposes a proactive quality assurance framework driven by Industrial Artificial Intelligence (AI), designed to enhance defect detection accuracy during ECU manufacturing. The approach integrates supervised machine learning models and anomaly detection algorithms trained on high-dimensional datasets collected throughout the production line and End-of-Line (EOL) functional testing. These models learn to identify complex, nonlinear relationships within test parameters that are indicative of potential ECU defects—often before the failure manifests during traditional testing procedures. A case study conducted in an operational automotive production environment demonstrates the efficacy of the system. The AI-based method achieved an increase in early defect detection rates by over 30%, while significantly reducing false positives, leading to improved operational efficiency and reduced manual rework. By enabling real-time, data-driven decisions, this methodology aligns with Industry 4.0 objectives and offers a scalable solution for predictive quality control in high-volume automotive manufacturing.

Keywords: Electronic Control Units (ECUs), Defect Detection, End-of-Line (EOL) Testing, Machine Learning, Supervised Learning, Unsupervised Learning, Random Forest, Support Vector Machines (SVMs), Autoencoders, Anomaly Detection, Quality Assurance, ASPICE Compliance, ISO 26262, Explainable AI (XAI), Edge Computing.

I. INTRODUCTION

Electronic Control Units (ECUs) are central to the operation of contemporary automobiles, managing essential systems such as braking, steering, engine performance, infotainment, and safety mechanisms. With the growing demand for vehicle intelligence, autonomy, and connectivity, the number and complexity of ECUs have increased substantially. A modern car often integrates dozens of these embedded systems, each contributing to the coordinated functioning of the vehicle as a whole. This increasing reliance on ECUs introduces significant challenges in manufacturing, where ensuring the functional integrity of each unit becomes crucial. Even minor inconsistencies or hidden flaws in hardware or software can escalate into critical failures, potentially compromising vehicle safety and leading to expensive warranty issues or recalls. Traditional quality assurance techniques, particularly those based on rule-based or threshold-driven testing at the End-of-Line (EOL), can identify clear defects but often miss more subtle indicators of potential failure—especially those that do not breach predefined thresholds or exhibit non-obvious patterns. Conventional testing strategies tend to be reactive rather than predictive, focusing on whether a component passes or fails specific predefined criteria. This binary evaluation method often overlooks underlying anomalies that might suggest emerging issues. Moreover, as vehicle electronics grow more intricate, the interdependencies between components make it more difficult to isolate causes of failure using only deterministic logic or manual analysis. This paper explores the AI within the ECU production and testing pipeline. By analyzing high-resolution test data from manufacturing and EOL stages using machine learning models, it becomes possible to uncover patterns and deviations that traditional methods may not detect. These AI models, which include both classification and anomaly detection algorithms, can learn from historical data to identify early warning signs of defects, enabling intervention before flawed units leave the factory. The objective of this study is to develop a proactive quality control system that integrates seamlessly with existing production lines, enhances detection capabilities, and minimizes false alarms. The framework is tested in a real-world automotive manufacturing environment to validate its effectiveness in improving overall quality assurance processes and reducing downstream failures.

II. BACKGROUND AND PREVIOUS RESEARCH

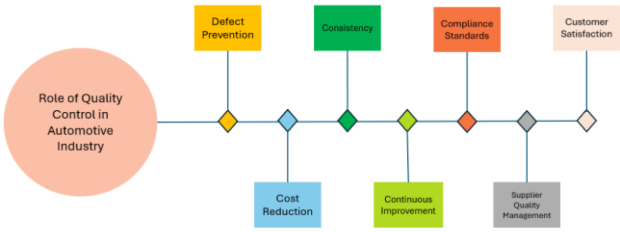

Fig. 1. *Role of Quality Control in Automotive Industry*
Fig. 2.

Conventional quality control (QC) methods in automotive manufacturing primarily rely on rule-based systems and threshold-driven tests to evaluate the functionality of components like ECUs. These systems, though effective at identifying obvious defects, tend to overlook more complex failure modes or subtle anomalies, particularly in highly integrated systems. Traditional methods also generally work reactively, detecting issues only when components fail certain pre-established criteria. As a result, problems that develop subtly or gradually in the production process may go unnoticed until later stages or after deployment, leading to safety risks and significant warranty costs.

In contrast, ML and AI have been applied increasingly to quality control in various industries, offering new potential for identifying defects. Specifically, AI has been widely adopted in predictive maintenance and anomaly detection for vehicles already in the field. For example, machine learning techniques like decision trees and support vector machines (SVMs) have been used to predict vehicle component failures by analyzing real-time data from in-vehicle sensors and diagnostic systems.

Although there has been considerable research into AI applications for in-field vehicle maintenance, fewer studies have applied AI directly during the manufacturing phase of automotive components, especially ECUs. The integration of AI into production lines, particularly for quality assurance, presents significant challenges, primarily due to the complexity and high dimensionality of the data generated during production and EOL testing. These datasets contain diverse features, including voltage, current, timing signals, and communication data between ECUs, which traditional rule-based methods are ill-equipped to handle comprehensively. A few studies have explored the potential of AI for quality control in the automotive production process, particularly in final testing. These systems often use supervised learning approaches, where labeled data is required for model training. While these methods can detect some known failure modes with good accuracy, they face challenges when handling more subtle issues or previously unseen failure types that might not have been part of the training dataset.

In addition, unsupervised learning methods, including clustering algorithms and anomaly detection models, have been examined in the context of industrial quality control. These approaches do not require labeled data, making them useful for detecting previously unknown defects or unusual patterns in complex systems.

Autoencoders, a type of neural network used for unsupervised anomaly detection, have been applied in manufacturing to detect deviations in production data that indicate potential defects [4], [5]. These models have proven effective in environments like semiconductor manufacturing, where the detection of minute, hidden faults is critical. However, their direct application to the automotive industry, particularly for detecting defects in ECUs during production, remains largely unexplored.

Supervised learning models, such as random forests and neural networks, have also been utilized in quality control in other manufacturing domains, but their application in ECU production is limited. For example, machine learning-based systems have been developed for electronic parts inspection, identifying out-of-spec components during assembly on production lines [6]. However, implementing such models in automotive manufacturing, where failure modes can be more diverse and less predictable, presents challenges, particularly in terms of acquiring sufficient labeled data for training purposes. The gap in applying AI-driven techniques during the production and final testing stages of ECUs has been a key driver for this research. While previous studies have predominantly focused on quality control post-production or in the field, this paper proposes a novel approach that integrates both supervised and unsupervised machine learning algorithms for proactive defect detection during the manufacturing of ECUs. This approach aims to enhance the identification of subtle and complex failure patterns that traditional testing methods often miss, ensuring more robust and efficient quality control in automotive production.

III. METHODOLOGY

This section describes the AI-driven approach applied to detect defects early in the automotive ECU production process. The proposed methodology integrates data collection, preprocessing, AI model selection, training, and validation to identify defects during production, improving product quality, reducing field failures, and lowering warranty costs.

A. Data Collection

The first step in this methodology is the comprehensive collection of data from multiple stages of the ECU production process. Each stage provides unique information relevant for detecting defects, which, when combined, forms a detailed representation of the ECU's behavior during production.

- Functional Testing: This phase involves verifying the core functionalities of the ECU. Data collected includes voltage levels, current readings, and sensor outputs, which are recorded during different operational states. These signals help confirm that the ECU performs as expected under standard conditions.
- Environmental Stress Screening (ESS): In this stage, the ECU is exposed to harsh conditions such as high temperatures, humidity, and vibration. These stress tests simulate real-world environments, and the data collected includes temperature and humidity measurements along with other stress-related variables. This information is critical for detecting faults caused by environmental factors.
- End-of-Line (EOL) Testing: EOL testing ensures that the ECU meets all functional requirements before it leaves the production line. The data collected includes communication bus messages (e.g., CAN bus data), which provide insights into how the ECU communicates with other components. Additionally, Diagnostic Trouble Codes (DTCs) are recorded to identify any faults or abnormal behavior. These signals help pinpoint defects that could lead to failures in the field.

By integrating these data streams, a comprehensive dataset is formed, including time-series data, categorical codes, and sensor outputs, which together provide a detailed picture of the ECU’s performance.

B. Preprocessing

Data preprocessing is an important step to gather the raw collected data for machine learning analysis. The goal is to clean, normalize, and transform the data to ensure it is suitable for training accurate and robust models.

- Data Cleaning: Raw data often contains noise, missing values, and outliers that can negatively impact model performance. To address this, missing data is handled using techniques such as imputation (e.g., replacing missing values with the mean of the column), and outliers are detected and removed using statistical methods.
- Normalization: Since the data collected spans multiple sensors with different units and scales (e.g., temperature vs. voltage), normalization is applied. Techniques like Z-score standardization or Min-Max scaling bring all features to a comparable range.
- Feature Extraction: Time-series data, such as voltage and sensor readings, are segmented into smaller windows to capture temporal patterns. Statistical features such as mean, variance, skewness, and kurtosis are calculated to summarize the data. These features represent key characteristics of the signals that can help identify defects.
- Dimensionality Reduction: High-dimensional data often contains redundancies and unsupported features that reduces the performance of machine learning models. Principal Component Analysis (PCA) is applied to reduce the number of dimensions while preserving most of the data's variance, thereby improving model efficiency and interpretability.

C. AI Algorithms

In this study, both supervised and unsupervised machine learning algorithms are utilized to detect defects in ECUs. Each model type serves a distinct purpose in the quality control process.

Supervised Learning: Supervised models are trained on labeled data, where each sample is marked as either a pass or fail, based on the outcome of the test. These models are well-suited for known failure modes, where historical labeled data is available.

- Random Forest: This ensemble learning method combines multiple decision trees to improve prediction accuracy. It is effective for handling high-dimensional data and capturing complex relationships in feature space.
- Support Vector Machines (SVM): SVM is a classification model that attempts to find a hyperplane that best separates classes in a high-dimensional feature space. It is well-suited for binary classification tasks, such as predicting whether an ECU will pass or fail.
- Neural Networks: Deep learning models, particularly feedforward neural networks, are employed to learn complex, non-linear patterns in the data. Neural networks are effective at modeling intricate relationships in the data, making them suitable for high-complexity production environments. models.

Unsupervised Learning: When labeled data is sparse or unavailable, unsupervised learning techniques are used to detect anomalies that may indicate defects.

- Isolation Forest: This anomaly detection method works by isolating data points that differ significantly from the majority of the data. It is particularly effective in high-dimensional datasets, where traditional distance-based methods struggle.
- Autoencoders: These neural networks are trained to compress data into a lower-dimensional representation and then reconstruct it. If the reconstruction error is high, it indicates that the input data is anomalous. Autoencoders are particularly useful for detecting previously unseen defects in the data.

D. Model Training and Validation

Training the AI models involves using historical production data, which serves as a representative sample of the conditions and outcomes observed during manufacturing. The training process aims to build models that generalize well to unseen data, avoiding overfitting.

- Training Data: The models are trained on data collected from previous production batches, which contains both normal and faulty ECU data. This allows the algorithms to learn the relationship between various features and the likelihood of defects.

- Cross-Validation: To assess model performance and reduce the risk of overfitting, k-fold cross-validation is applied. In this process, the dataset is split into k subsets, and the model is trained k times, each time using a different subset for validation. This approach ensures that the model is evaluated on all available data, improving its robustness.
- Performance Metrics: The effectiveness of the models is evaluated using several metrics, including:

Accuracy: The proportion of correct predictions (both pass and fail).

Precision: The fraction of predicted defects that are actual defects. This metric helps reduce false positives.
Recall: The fraction of actual defects identified by the model. This metric helps ensure that defects are not overlooked.

The proposed methodology leverages AI algorithms to detect defects in ECUs early in the manufacturing process, enhancing quality control efforts in automotive production. By combining data from functional tests, environmental stress tests, and EOL testing, and using both supervised and unsupervised learning models, the system identifies subtle anomalies and reduces the likelihood of defects reaching the field. The data preprocessing steps, along with robust model training and validation techniques, ensure the system's reliability and effectiveness in real-world production environments.

IV. SYSTEM ARCHITECTUREAND AI INTEGRATION FRAMEWORK

This section details the architecture and framework necessary to deploy AI models effectively within the ECU production environment. The system integrates data from various stages of the production process, applies advanced preprocessing techniques, runs AI models for defect prediction, and supports real-time decision-making. The architecture is designed to be scalable and accommodating multiple ECU variants across different production lines. It combines edge computing for real-time data analysis with cloud computing for model updates and retraining, ensuring both immediate defect detection and long-term adaptability.

A. Data Collection from Test Benches

Data collection in ECU manufacturing begins at test benches during functional testing, environmental stress screening (ESS), and End-of-Line (EOL) testing. Functional testing verifies core ECU operations through electrical measurements (voltage, current, sensor outputs). ESS subjects ECUs to environmental extremes (temperature, humidity, vibration) to detect stress-related issues. EOL testing ensures network communication via CAN messages and captures Diagnostic Trouble Codes (DTCs). Data from all phases is consolidated into a unified repository for comprehensive performance evaluation.

B. Preprocessing Pipelines

The Collected data undergoes preprocessing to ensure quality and consistency for AI analysis. This includes data cleaning (imputation, outlier removal), normalization (Z-score, Min-Max scaling) to standardize sensor outputs, and feature engineering to extract statistical descriptors from time-series data. Dimensionality reduction techniques like PCA are applied to eliminate redundancy and improve computational efficiency while preserving critical information.

C. AI Models for Defect Detection

The AI models analyze preprocessed data to detect ECU defects using both supervised and unsupervised approaches. Supervised models, such as Random Forests, SVMs, and Neural Networks, are employed when labeled data is available, enabling accurate classification of pass/fail outcomes. In contrast, unsupervised models like Isolation Forests and Autoencoders are used when labels are limited, identifying anomalies through pattern recognition. These models collectively enable robust defect detection across diverse data scenarios.

D. Model Inference and Edge Computing

The Trained AI models are deployed on edge devices (GPUs, FPGAs) for real-time inference directly on the production floor. This local processing minimizes latency, enabling immediate pass/fail predictions and rapid intervention. As new test data is collected, edge devices execute the models and trigger alerts upon defect detection, supporting timely corrective actions.

E. Cloud Integration for Model Updates and Scalability

The cloud supports system scalability and continuous model improvement. It enables large-scale model training and retraining using accumulated data, with updated models deployed back to edge devices. The cloud also serves as a central hub for data storage and analysis, facilitating trend detection and performance monitoring. Additionally, it allows scalable deployment across multiple production lines and ECU variants, ensuring system flexibility.

F. Decision-Making and Production Line Integration

Following model inference, the system initiates actions based on defect predictions. Automated alerts notify operators and provide diagnostic details such as DTCs to aid in troubleshooting. The AI system is tightly integrated with production workflows, enabling automatic rerouting or flagging of defective ECUs for inspection, preventing faulty units from progressing further. Additionally, the system incorporates a continuous learning loop, where feedback from identified defects is used to retrain models, allowing them to adapt to evolving production conditions and emerging defect patterns.

V. COMPARATIVE EVALUATION OF AI MODELS FOR DEFECT DETECTION

In this section, we compare and evaluate the performance of various machine learning models applied for defect detection in the production of Electronic Control Units (ECUs). Specifically, we analyze models based on their accuracy, computational efficiency, and robustness. These performance criteria are critical in assessing the feasibility and effectiveness of deploying AI in manufacturing environments. The models tested include Random Forest classifiers, Support Vector Machines (SVM), and Autoencoders. Each model has distinct characteristics that make it suitable for particular types of data and defect detection tasks.

A. Random Forest Classifier

The Random Forest classifier is an ensemble learning method that combines multiple decision trees to improve prediction accuracy and generalization. It is particularly effective for structured data, where clear feature importance can be extracted.

Performance: Random Forest classifiers demonstrated strong classification performance in identifying defects in the ECUs, especially when working with high-dimensional sensor data. The ensemble approach mitigates the risk of overfitting, making it a reliable choice for defect detection tasks.

Strengths:

- High Accuracy: Random Forests are highly accurate in both training and validation phases, consistently delivering good results when the data is structured and contains many relevant features.
- Handling of Large Data: The model can handle large datasets efficiently and provides useful insights into feature importance, which can help identify critical parameters that affect the quality of ECUs.
- Robustness to Overfitting: By using multiple decision trees and averaging their outputs, Random Forest classifiers are less susceptible to overfitting, making them ideal for environments with noisy data.

Limitations:

- Computational Expense: The ensemble nature of Random Forest models can lead to increased computational complexity, especially when the number of trees in the forest is large or when dealing with very high-dimensional data.

- Interpretability: While feature importance can be extracted, understanding the decision-making process of Random Forests can still be challenging, making it less transparent compared to simpler models.

B. Support Vector Machines

SVMs are supervised learning models that find the optimal hyperplane to classify data into distinct categories. They are known for their ability to work well in high-dimensional spaces and handle complex, non-linear data distributions.

Performance: SVMs excelled in defect detection, especially when the data exhibited complex patterns or non-linearity. Their performance was strong across both training and testing datasets, particularly when the data was high-dimensional, making them effective for defect detection when sensor data has multiple features.

Strengths:

- Strong Generalization: SVM models are effective at generalizing to unseen data, which is important in automotive production where unseen defect types may occur.
- Handling Complex Data: SVMs use the kernel trick to map data into a higher-dimensional space where it is easier to separate classes, making them robust in situations where data is not linearly separable.
- Control of Overfitting: By adjusting the regularization parameter, SVM models can effectively control overfitting, ensuring that the model is neither too simple nor too complex.

Limitations:

- Training Time: Training SVM models can be time-consuming, especially when dealing with large datasets or complex feature spaces. This could limit their real-time applicability in fast-paced manufacturing environments.
- Parameter Sensitivity: SVM models require careful selection of hyperparameters (C and gamma), which can influence model performance. Tuning these parameters may require significant computational resources.

C. Autoencoders

Autoencoders are unsupervised neural networks that learn efficient representations of data by compressing and reconstructing it. They are commonly used for anomaly detection, as the reconstruction error can be used to identify outliers or defects.

Performance: Autoencoders are particularly effective at detecting rare anomalies, making them ideal for scenarios where defects are infrequent or not well-represented in the training data. They work by learning the patterns of normal behavior and highlighting deviations as potential defects.

Strengths:

- Effective for Anomaly Detection: Autoencoders are highly effective in detecting anomalies in data, especially when defect patterns are rare or not labeled, which is often the case in production environments.
- Adaptability: They can handle a variety of data types, including time-series sensor data, and learn to reconstruct inputs that are normal, making them flexible in detecting a wide range of defects.
- Unsupervised Learning: Autoencoders do not require labeled data, which is useful in situations where obtaining labels is expensive or time-consuming. They can be deployed in environments where labeled defect data is sparse.

Limitations:

- Training Complexity: Autoencoders can be difficult to train, particularly with large or noisy datasets. Selecting the appropriate network architecture and tuning parameters can be challenging.
- Sensitivity to Noise: While autoencoders are great for anomaly detection, they may struggle in noisy environments. High levels of noise can cause incorrect anomaly detection or miss subtle defects.

- Black Box Nature: Similar to other deep learning methods, autoencoders operate as "black boxes," making it difficult to interpret their decisions. This lack of transparency can be a concern for real-time quality control systems in production lines.

VI. DATA ENGINEERING CHALLENGES IN ECU DEFECT DETECTION

Effective data engineering is essential for deploying AI models in Electronic Control Unit (ECU) defect detection. Various challenges arise from the characteristics of the data, including imbalanced class distributions, noise due to environmental variability, and inconsistent labeling. Overcoming these issues requires robust preprocessing techniques and innovative learning methods.

A. Imbalanced Class Distributions

ECU defect datasets are typically imbalanced, with far more non-defective units than defective ones. This imbalance can create models that are biased toward predicting the majority class (non-defective). Synthetic Minority Over-sampling Technique (SMOTE) helps by generating synthetic examples of defective units, balancing the dataset and improving defect detection. While useful, SMOTE should be applied cautiously to avoid overfitting, which can diminish the model's generalization ability.

Alternatively, under sampling the majority class can balance the dataset but risks losing valuable information. A combination of oversampling and under sampling can sometimes offer the best trade-off.

B. Noise from Environmental Variability

Environmental influences such as temperature fluctuations and electrical interference introduce noise into sensor data. This can make defect detection difficult, as the noise might be mistaken for a defect. Signal filtering techniques, such as low-pass filters and moving averages, can smooth out noise and highlight significant trends. Additionally, robust machine learning models, like Random Forests, can handle noisy data more effectively by focusing on the most relevant features.

C. Inconsistent Data Labeling

Inconsistent or inaccurate labeling of defects can also impede model performance. Human error, sensor calibration issues, or discrepancies in defect categorization can lead to mislabeled data. To mitigate this, it's important to implement standardized labeling procedures and automated validation systems that ensure consistent and accurate labels. In cases where full labeling isn't feasible, semi-supervised learning approaches can be valuable. These models use both labeled and unlabeled data, improving accuracy and robustness even when defect labels are sparse.

D. Semi-Supervised Learning

Semi-supervised learning is particularly useful when labeled data is limited. By using a small set of labeled examples and a larger set of unlabeled data, semi-supervised models can improve their generalization capabilities. Techniques like self-training, where the model labels its own data, and co-training, which involves using multiple models to validate each other's predictions, can help enhance performance even with sparse labeled data.

In summary, the data engineering challenges in ECU defect detection require careful attention to data imbalances, noise, and labeling inconsistencies. Techniques like SMOTE, signal filtering, and semi-supervised learning offer practical solutions to these issues. By addressing these challenges effectively, manufacturers can deploy more reliable and efficient AI-driven defect detection systems, ultimately improving product quality and reducing costs.

VII.INDUSTRY ADOPTION OF AI IN ECU PRODUCTION AND COMPLIANCE CONSIDERATION

The use of AI in automotive manufacturing, especially in the production of ECUs, is rapidly expanding. AI offers significant advantages in improving defect detection, enhancing quality control, and increasing manufacturing efficiency. However, as AI is integrated into production workflows, it must adhere to key industry standards, including ASPICE and ISO 26262, ensuring safety, reliability, and regulatory compliance.

A. Industry Adoption Trends

AI is increasingly being used across automotive manufacturing to improve defect detection and optimize production processes. In the context of ECU production, AI technologies help identify defects that may not be visible with traditional methods, using data from testing stages like functional testing and EOL checks. By predicting failures before they happen, AI reduces costs, minimizes downtime, and ensures product quality. The adoption is driven by the need for more efficient, cost-effective manufacturing methods as ECUs become more complex.

B. Compliance with Standards

AI applications in ECU production must comply with critical standards like ASPICE and ISO 26262:

- ASPICE (Automotive SPICE): This standard assesses and improves automotive software development processes. When AI is used for defect detection, it must integrate into production processes that adhere to ASPICE's rigorous guidelines for software quality and testing.
- ISO 26262 (Functional Safety): This standard is designed to ensure the functional safety of electronic systems in vehicles. For AI to be safely applied to ECU testing and defect detection, it must be validated rigorously to guarantee that it operates safely and reliably in all conditions.

Both standards emphasize traceability, validation, and auditing, which ensures that AI-driven systems are safe, transparent, and accountable in the production process.

C. Safety and Reliability Concerns

AI systems used in ECU production must meet high standards for safety and reliability. Black-box models, such as deep learning, can pose challenges in safety-critical applications because they often lack transparency. To address this, adopting explainable AI (XAI) methods can provide insights into the decision-making process, ensuring that the AI's actions can be understood and verified. Additionally, AI models must be robust enough to handle environmental variability, like temperature or electrical interference, which can introduce noise into data.

D. Best Practices for AI Deployment

To successfully integrate AI in ECU production while maintaining compliance, manufacturers should follow these best practices:

- Thorough Testing and Validation: AI models should be rigorously tested to meet industry standards like ASPICE and ISO 26262, ensuring their performance and safety.
- Explainable AI: To address transparency concerns, AI models should be designed with interpretability in mind, ensuring that their decisions can be traced.
- Continuous Monitoring: Regular monitoring and auditing of AI models are essential to ensure they continue to meet safety and performance standards throughout their lifecycle.
- Redundancy and Fail-Safe Systems: AI systems should be backed by additional safety mechanisms to ensure that defects are not missed, and the production process remains uninterrupted in the event of AI system failure.

E. Future Trends

As AI adoption continues to grow, multi-plant training pipelines will become essential for scaling AI across production facilities. These pipelines will allow models to be trained on data from different locations, improving their adaptability and performance in diverse environments. Additionally, federated learning a method that enables AI models to learn from local data without transferring sensitive information will help manufacturers train models while ensuring data privacy and compliance with data protection regulations.

VIII. CONCLUSION AND FUTURE WORK

This This paper introduces a new framework that leverages Artificial Intelligence (AI) to detect defective Electronic Control Units (ECUs) early in the production process. The proposed methodology enhances quality control by identifying failure modes that traditional testing methods might miss. By using both supervised and unsupervised learning techniques, the AI system significantly improves defect detection accuracy, reduces the rate of false positives, and ensures better product quality. Furthermore, the approach helps reduce manufacturing costs by addressing defects earlier in the process, which minimizes the need for costly rework and recalls. It also ensures compliance with industry standards such as ASPICE and ISO 26262, which are critical for safety and reliability in automotive production.

As the use of AI in manufacturing continues to evolve, several areas offer opportunities for further advancement. One key direction for future development is the integration of real-time AI deployment on production lines. By enabling AI models to function during live testing on test benches and in real-time production environments, manufacturers could achieve instant feedback and corrective actions, optimizing production efficiency and reducing downtime. This would also allow the system to continuously monitor and detect defects, further enhancing the overall reliability and speed of production.

Another promising direction is the adoption of federated learning, which would enable the training of AI models across different production sites without requiring the transfer of sensitive data. This decentralized approach would help improve the model's generalizability by incorporating diverse datasets from multiple locations, ensuring compliance with data privacy and regulations. Federated learning could be particularly beneficial for manufacturers operating on a global scale, allowing AI models to learn from a wide range of production environments.

Moreover, expanding the current framework to include a broader range of ECU variants is essential. As vehicles become more complex, incorporating additional systems like infotainment, ADAS, and various powertrain components, the ability to adapt the defect detection framework to various types of ECUs will be critical. This flexibility will make the system more scalable, allowing manufacturers to use it across different product lines and vehicle models.

In addition to enhancing defect detection, the integration of the AI framework with predictive maintenance systems could provide even greater value. Predictive maintenance technologies rely on historical data and real-time sensors to forecast potential failures, allowing manufacturers to take corrective actions before issues arise. Combining defect detection with predictive maintenance would not only improve product quality in the short term but also contribute to the long-term reliability of the vehicle systems.

Furthermore, ensuring the robustness of the AI models under varying environmental conditions is a critical consideration for the future. Environmental factors like temperature changes, electrical interference, and other forms of noise can affect sensor data and influence defect detection. Future AI models must be trained to handle these variations, making them more reliable in real-world production environments.

Finally, ongoing collaboration with industry partners manufacturers, suppliers, and regulatory bodies will be vital to refine the framework and ensure its alignment with industry requirements. This partnership will help address real-world challenges, evolve the system in response to new technological developments, and ensure that the AI models meet the rigorous safety and quality standards required in automotive production.
In conclusion, the AI-based framework presented in this paper represents a significant step forward in improving quality control in ECU production. The proposed system not only enhances defect detection but also reduces costs and improves manufacturing efficiency. Future advancements, including real-time deployment, federated learning, and the ability to handle multiple ECU variants, will drive the continued

evolution of AI in automotive manufacturing, paving the way for even higher levels of safety, reliability, and operational efficiency.

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