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End-to-End Traceability and Defect Prediction in Automotive Production Using Blockchain and Machine Learning

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Abstract
With the increasing number of digital technologies in production, more and more detailed product data can be collected, measured, and analyzed. Coupled, this forms the basis for future data services during the product life cycle. In this way, suppliers, OEMs, and vehicle users achieve a new quality and transparency of their respective internal value chains and enable completely new improvements. However, many of the current product data services only serve specific services or partial aspects of a vehicle with a digital twin but do not enable an overall continuous digital profile. One reason is the multitude of different systems in the automotive data landscape and along the entire product line, from product design to the end of life.
In addition, the vulnerability of the data increases with each touchpoint in the value chain and thus in the field use. Missing transparency and trust of data are also major challenges for companies and users beyond the vulnerability of blockchain-based in-vehicle data use and thus also hamper the potential of a new era of collaboration and cooperation structures in the use of new digital technologies in production. This research aims to conceptualize a design approach for continuous and reliable data for the overall digital product profile along the entire product life cycle. In doing so, a design and validation approach for an overall digital product profile based on the integrated automation of blockchain technology and machine learning is developed and the individual areas of action are demonstrated in a concrete demonstrator. Virtual product twins in combination with structural digital twins should enable the new quality of end-to-end traceability and defect prediction as part of the overall digital product profile for automotive OEM data services, supplier services, and customers.

Keywords: Digital Technologies, Product Data, Product Life Cycle, Data Services, Digital Twin, Automotive Industry, Value Chain Transparency, System Integration, Data Vulnerability, Blockchain, Data Trust, Collaboration Structures, Continuous Digital Profile, Machine Learning, Automation, Virtual Product Twins, Structural Digital Twins, End-to-End Traceability, Defect Prediction, OEM Data Services.

1. Introduction

The automotive industry is a key sector for the welfare and development of many economies around the world. Continuous innovation is essential for ensuring the attractiveness and sustainability of the domestic automotive market. The utilization of new technologies in production processes is an essential guideline of the strategy defined by major automotive manufacturers, with investments focused on advanced electronic systems and new-generation products. The presence of faults on vehicles that pass quality inspection impedes the objectives of reducing costs and time and increasing quality and efficacy. A significant reduction of product defects is not a simple task, especially in the high-tech products of the automobile industry. Digital transformation in these complex and highly interlinked industrial ecosystems makes communication, collaboration, and integration of all supply-chain participants crucial to securing real value. Control over the whole product lifecycle and the secure, generalized manipulation of data is actively promoted by the emergence of blockchain technology.

First-generation Blockchains were designed to securely store unchangeable data for digital currencies. Recent developments led to Private Permissioned Blockchains, suitable for storing immutable product data locally and highlighted for usability in product traceability and supply chain management. On the other hand, the recent Machine Learning revolution allows the extraction of strong prediction models from the huge quantities of data available. Implicitly defective and mistakenly classified pieces can be detected with unsupervised Learning Classification Algorithms. This paper puts forth an integrated Data Science analysis using Private Permissioned Blockchains and Machine Learning to secure end-to-end product traceability and defect prediction on all the work performed in an automotive production plant floor. The complete process of a product is stored in a Permissioned Blockchain.

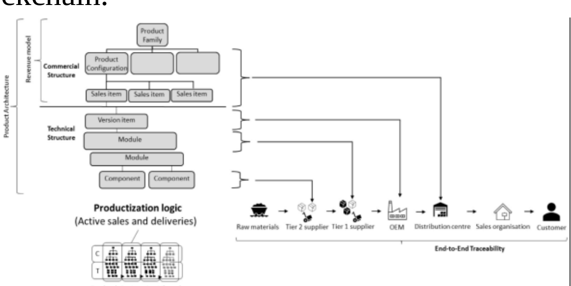

Fig 1 : Productization in End-To-End Traceability

1.1. Overview of the Study's Objectives and Scope

Currently, excess waste and high defect rates are common in automotive manufacturing, making it important to improve object and defect traceability to achieve zero-defect production. End-to-end traceability is currently difficult, as it requires a reliable and centralized data source that can be used to track parts from different suppliers through manufacturing and testing stages. However, it is particularly difficult to deliver a reliable and centralized solution for end-to-end traceability because there is no established "one-stop" or specialized defects testing process in automotive manufacturing. Furthermore, no solution has so far been integrated from defect prediction to defect resolution with end-to-end traceability in the automotive industry. The limitations of existing approaches lead to an increasing adoption of blockchain and machine learning technologies in the automotive sector. A blockchain network functions as a secure decentralized database for recording and validating data transactions while machine learning algorithms are capable of picking up hidden patterns from historical defect data to predict defects. Considering the aforementioned factors, this paper addresses the challenge of enhancing automotive production by exploring the technological integration between blockchain and machine learning. In particular, the goal of the research is to extend end-to-end defect traceability in automotive production by deploying a blockchain-based network and image data from machine learning-based defect prediction models. To achieve this goal, the study designs a blockchain architecture that serves as a data-sharing platform for automotive manufacturers and their suppliers to deploy defect prediction, which establishes a connection between defect identification and resolution across all relevant parties. This allows defect prediction results to be shared between network participants and used to prevent defect recurrence. This paper details the workflow of the proposed blockchain network with a focus on machine learning integration for additional defect prediction enhancement. The network addresses the three aspects of organization and operations, technical foundation, and security to create a solution that is specialized for automotive production. The study then demonstrates the viability of the proposed blockchain network.

2. Background

We present the background theory for production defect prediction and defect cause traceability. We describe the methods used to realize these two features in our solution, as well as the relevant concepts, especially in blockchain solutions and machine learning.

Traceability refers to the ability to access the production history of an individual product or production component. In automotive or similar assembly production, high-level product traceability is indicated by its unique VIN or similar. Each VIN may be associated with several documents defining its unique features and describing the assembly process, including for example the assembly steps and required or method times, the unique set of components used, and the assembly workers and staff. The document may also define additional parameters, e.g. the assembly shop floor environment conditions such as noise, temperature, humidity, vibrations, and air composition.

These assembly parameters are relevant because they may affect the defect probability of this VIN-unique product. Thus, by linking the assembly conditions and process with the produced parts, we can reasonably increase the defect prediction accuracy of any statistical model that works by linking the part parameters with the assembly parameters. By improving the prediction results quality of the zone model restricted to highly defect probable zones of the input space, we can improve the defect prediction results by developing a mixture of zone models of the input space, for example, a mixture of Gaussians.

In plain words, small part feature variations may hide large differences in assembly robustness. We can exploit the model by performing a zone recruitment based generalization, i.e. locally performing predictions or estimations with a subset of the mixture models. This concept is a cornerstone on machine learning models. By associating the input space zones with the model's internal parameters, we can apply the mixture of model concepts to any machine learning model.

Equation 1 : Traceability Confidence Score

$$T_c = \frac{N_v}{N_t}$$

Where

T_c: Traceability Confidence

N_v: Number of Validated Transactions on Blockchain

N_t: Total Production Transactions Logged

2.1. Automotive Production Overview

The automotive industry has undergone the most rapid transformation in its over 100-year-long history, accelerating its efforts to enable the use of more automation and advanced technology in the design and production of vehicles. The need for highly educated engineers and technicians is greater than ever to drive the technological advances necessary to enable this rapidly changing environment. Globalization is increasing the size and scale of automotive companies, from design to production and distribution. In addition to vehicle manufacturing plants, the automotive supply chain is a high-mix and high-volume organization with manufacturing plants around the world. Daily changes in various dimensions of the financial and product marketplace add complexity and dynamics to managing the supply chain.

The economy is in constant flux, and changes in demand factor into the automotive sector. Emerging economy countries that are investing heavily in building infrastructures increase the demand for light trucks. Demand for small, fuel-efficient cars also escalates in response to sustained and rising energy costs. No matter how efficient the production of goods itself, if demand is too great for the sector to manage, the organizations worldwide will fall short, impacting customers, stakeholders, and profits alike. Concurrently, the manufacturing organization is becoming a monolithic supplier to the automotive sector itself. As a direct cause, the demands associated with automotive production are higher than in any other sector, focused on specifications, volume, timing, and price.

Nevertheless, adding to the strain in the sector is sheer magnitude and risk associated with failure to meet timelines and visible quality levels. Ranking second behind the defense industry in the development of product technology risk, the profits in the sector are narrower than the high technology norm, added to the need for extensive investment to develop products. Failure in either product development or ongoing changes in product or manufacturing operations at production plants results in visibility and consumer impact far beyond any other technology sector.

2.2. Importance of Traceability

Automotive products made of hundreds of thousands of parts are assembled in production plants with a drive for the best quality possible. In contrast to the early days of mass production, where a single company built a car from production start to delivery finish, the majority of components are now built by specialized first-tier suppliers, using tooling and techniques developed by the automotive manufacturer. This fact resulted in a relatively small amount of volume production compared to the resources invested. Given the size and relative complexity of such systems, both the product and the production process are intensely scoped for quality concerns, including risk assessments, failure mode, effects analysis, and the statistical methods of Six Sigma, among others.

Traceability can be stated as the ability to track a product and/or its associated information throughout the entire production cycle. In recent decades, a multitude of traceability methods have been developed for both production and product usage phases. Traceability data provides access to a wealth of product information during the production stage, such as the individual products or batches as part of a process. This data is used to enhance product quality through statistical process control and the detection of anomalies in the process data. Defective products can be examined in detail, while known bad or good products from an automated process can be sent for additional examination. Sensors are also used to detect part-specific anomalies during the production process, such as changes in private attributes.

With the transition to product platforms, where many closely related products are built on a small variety of common vehicle architectures, the analysis of batches of defective products can provide valuable lessons for the improvement of the production process, tooling, and measured attributes. Such lessons are used to increase overall quality while concurrently decreasing the cost of defective product medical support, through additional testing and monitoring puesta in service activities.

2.3. Defect Prediction Methods

In recent years, the desire for flexible manufacturing and competitive prices has caused the automotive manufacturing industry to become increasingly customer-oriented. New technologies related to Industry 4.0, which uses machine learning techniques, the Internet of Things, and sensor data, allow for far more dynamic changes to be made in real time. This now forces automotive companies to focus on more than just predictive analysis, as had been done in the past. These companies must also consider the success of adaptive recommendations, thus providing actual business benefits through enhanced quality engineering. For instance, in engine assembly lines, misaligned air – compressor ducts or incorrectly seated air – compressor module bolts may result in engine vibration and noise. Many other defects during the assembly or even production of various components such as body, chassis, and engines cause customer complaints. Multi-job assembly lines constantly adjust to customers' demands can cause serious yet manageable defects.

Research and industrial development show that implementing industrial image processing solutions helps reduce and control defects. Overview of existing defect detection methods on production lines. Three pertinent approaches to factory image analysis are inspection, location, and recognition. The recognition approach aims at the object level in which one or a few objects of the same kind are recognized, their partial and fragile structure studied, allowing for modular plans. In the location approach, one or a few objects of the same kind are located, allowing for instancing strategies. In the inspection approach, all objects present in an image are predicted and inspected, and their global structure is analyzed. Such production line defect detection systems need prior initial training because of the appearance of unknown defects and potential production line changes. Even with appropriate training, prediction is known to suffer from challenging complex backgrounds, perspective effects, occlusions, motion blurriness, and the viewpoint-invariance problem.

2.4. Blockchain Technology in Manufacturing

The advent of Industry 4.0 in manufacturing proposes a new form of industrial paradigm. Innovative solutions that rely on key technologies are propelling smarter factories by promoting automation, efficiency, interconnectivity, and autonomy. Furthermore, many industry proposals have focused not only on serving production efficiency but have also started incorporating quality and product features into their solutions. Among them, the deployment of two key technologies has started disclosing a new era in manufacturing: blockchain and machine learning. These two technologies combined are closing the gap between the physical and the digital worlds, serving as enablers for the vision of a smart factory.

Blockchain is a decentralized form of digital ledger technology where information is relatively stored in multiple nodes of a peer-to-peer network, where no authority oversees it. This technology has attracted attention due to the robust security features and the transparency that it provides as a result of its immutability property. Security and transparency, however, must be implemented for only part of the information contained in the blockchain since it is not always recommended to store sensitive data for enterprises or clients due to privacy policies. The Blockchain is primarily being adopted in the areas of logistics and supply chain and also as a way to protect intellectual property. Blockchains are mainly combined with the Internet of Things and RFID technology, thus boosting tracking capabilities across the whole life cycle of the product.

2.5. Machine Learning in Quality Control

Machine learning methods are now being widely applied in many aspects of manufacturing, particularly for quality control. While industrial applications use fully supervised learning systems that require massive amounts of labeled training data to be useful in defect detection, these may not be available. One common scenario is that “good” products are excessively labeled, while defect data is short or non-existent. In this case, semi-supervised learning (SSL) is useful, as it takes advantage of the good class labels and the generative power of unsupervised techniques such as deep learning, while also incorporating the defect information if even a small number of labeled examples are available. A variety of semi-supervised techniques have been used for image classification.

Another common scenario in quality control is that defect classes are rare, and a model trained to weigh equally all the types of defect may underperform. For these cases, there are corrective measures that may be taken, such as data augmentation or resampling of rare classes with over or undersampling. Indeed, both of these techniques can be combined in both the training and evaluation processes. In addition to detecting defects, ML methods have been used to predict the quality and reliability of products from high dimensional measurements. Though QA/QC systems were previously constructed with careful feature engineering, ML systems can be trained with the entire excess dimensionality usually present in such measurements.

In some applications, such as high-dimensional data from electrochemical impedance spectroscopy, continual retraining with accumulating new data is feasible and allows for systematic tracking of quality as the production process evolves. Finally, ML methods allow for and improve the efficiency of, some newest innovative non-destructive testing techniques that allow for real-time online monitoring of manufacturing operations.

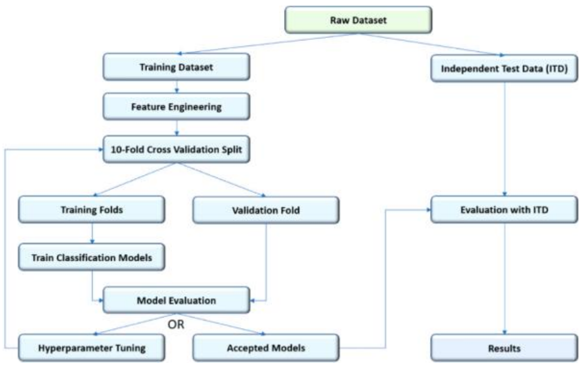

Fig 2 : Machine Learning Methods for Quality Prediction in Production

3. Literature Review

This section analyzes relevant previous work on the two main topics of our study: automotive defect detection and prediction, and the integration of blockchain and machine learning to enhance system performance. First, we will present the literature on defect tracking in production or development. Then, we will provide an overview of the most used algorithms for machine learning-based defect detection. Finally, we will present the research on the integration of blockchain with ML techniques.

1. Previous Work on Traceability

Several scholars deal with the traceability task, mainly based on the automotive industry. Such systems could use several approaches to create the data connection. A classic one is based on the creation of a tree of defects, where the defect detection depends on how many lower-level defects exist: the more defects, the higher the chance to link a new defect with the parent or principal one. Other approaches are centered around the data description quality. One proposes an improvement in the quality of the description based on expert knowledge combined with data mining methods, while another proposes a technique based on NLP tools. Finally, it is proposed that deep learning combined with the software environment metadata would be sufficient for the tracking task as long as some prerequisites are achieved. Notably, the tracking phase itself is never proposed to be automatic by any authors. Some authors, when dealing with the traceability task, center their research on the type of described defects or their severity.

2. Defect Prediction Techniques

Regarding the prediction phase, the available research uses several machine learning techniques, with ML networks, Naïve Bayes classifiers, and support vector machines being the most described, and there are also reports on the use of deep learning techniques. These techniques are not used to the exclusion of other statistical approaches or heuristic methods, and in some cases, hybrid algorithms are adopted. It is also normal for researchers to analyze data from several sectors other than automotive and, when analyzing how predictions could improve over time, to make predictions after specific time increments rather than generating predictions limited to the analysis data employed. Finally, we noted that several scholars claimed to improve the prediction phase by enriching the data with additional sources.

3. Integration of Blockchain and Machine Learning

Blockchain can serve many purposes for ML to perform maximally, including data rarity, decentralized data storage, increasing data access, establishing a decentralized information marketplace, etc.

3.1. Previous Work on Traceability

Traceability is an essential function within an organization and is considered the backbone of quality management for any product, including the automotive industry. Traceability within the automotive sector is regulated by standards, along with a few specific regulations imposed by local authorities and clients. As it relates to process and system cost reduction, an organization with accurate traceability implementation would witness lesser product creep and misdirection. Within the product lifecycle, the automotive industry is highly dependent upon third-party suppliers for both the hardware and software. Regulations require the automotive original equipment manufacturers (OEMs) and suppliers to establish accurate data gathering to comply with traceability laws and to assist with root cause analysis for a failure. Any traceability solution within such a complex supply network (OEMs, tier 1, 2, and 3) would demand the integration of both physical and virtual processing spaces within the organization. Blockchain technologies have emerged, providing asset provenance, and helping organizations to establish tamper-proof records of their information. They have also created new opportunities to provide a new level of protection against data loss or data leakage.

Blockchain-based traceability applications are being actively investigated, with several proofs of concepts, pilot implementations, and experimental benchmarks being published. Domains, such as authenticity verification and records management have shown success in using a blockchain-based approach. In the automotive domain, issues of product liability, asset management, and electronic health record storage are all use cases for blockchain technologies. Despite the benefits, research in this domain is still limited. Current offerings are often piloted systems with a narrow focus on non-automotive issues, except warranties and health records. Within the automotive domain itself, these solutions have not been integrated into a complete ecosystem with other enterprise systems involved within the data collection use case.

3.2. Defect Prediction Techniques

To widen the recuperation scope of large amounts of data collected in factories, several companies have started to apply Machine Learning (ML) and Artificial Intelligence (AI) methods to predict product, process, and system phases where defects are occurring. Companies shall not only collect data but also use it to train algorithms that address specific questions. Most existing ML-based defect prediction techniques normally use surface profiles as their input. However, there exist only a few works that utilize ML models for defect prediction in general industrial applications. In most cases, the fastest method with the highest accuracy is preferred. The use of transfer learning and neural networks are successful approaches.

A decision tree classifier is proposed to predict defects on phosphor bronze connectors. Various sets of manufacturing data with defect samples covering up to 10 years of production data are analyzed. Inputs to the model include the product type, material, number of terminals, lifetime in days, visual inspection, humidity, and temperature condition. The model accuracy is highly dependent on the selected features. Typical features used in similar studies are also mentioned. Due to the effects of uncontrollable external process conditions, the defect rates in a mass production process typically vary for different batches of products. In the specific case of wafer-level packaging for MEMS microphones, Hidden Markov models are utilized considering that due to the temporal correlation of the defect rates, the problem should be treated as a time series prediction.

3.3. Integration of Blockchain and Machine Learning

To overcome the challenges posed by such systems, we propose the use of blockchain technology combined with machine learning. Blockchain is a decentralized, distributed ledger containing records of credible transactions that cannot be altered or deleted. Blockchain allows for a tamper-proof system for transaction logging among partner companies. Each transaction is stored inside a block that is connected and encrypted with a cryptographic hash function to form a chain. Each user operates their copy of the blockchain system, which creates a level of security through redundancy. Hence, every user in a particular system should have visibility and access to the logs. However, this is not true for every blockchain model. Public blockchains maintain redundancy across the entire network, making any disruption very costly and hence not worth it for the miners. Private or consortium blockchains allow specific parties in an ecosystem to access the logs while maintaining the same level of security as public blockchains.

Machine learning is being used as an improved version of expert systems. With the massive amount of data generated by IoT systems, machine learning can learn from the data and determine routes of action to reduce defects or downtime without human intervention. However, for the system to be effective, the algorithm must have visibility of all the data; otherwise, the system may not be as effective. Having access to past fault data from multiple partners in the automotive ecosystem would allow the machine-learning model to verify predictions using similar vehicles across manufacturers.

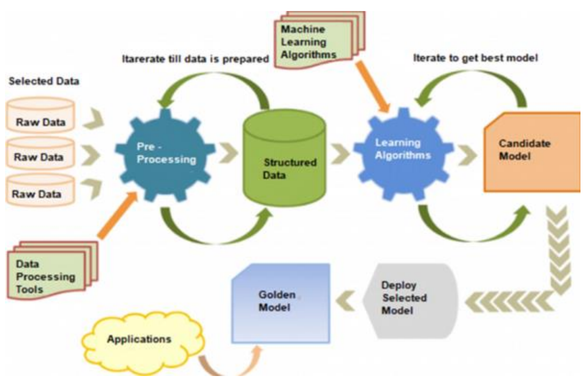

Fig 3 : Blockchain meets machine learning

4. Methodology

1. Research Design This research has adopted a triangulation strategy to provide and offer accurate details of our study in the context of defect prediction in automotive production. We employed quantitative analysis for defect prediction and qualitative analysis for the design of end-to-end traceability with a blockchain-based architecture in automotive production. Therefore, this study contributes to a quantitative basis for defect prediction based on multiple real-world datasets of increasing magnitudes. Furthermore, defect prediction is performed with an algorithm based on a rotation forest classifier that utilizes a novel hybrid measure established by a combination of the Chi-square test and Fisher discrimination ratio to select relevant features efficiently.

2. Data Collection and Sources Considering the lack of open datasets addressing defect prediction in automotive manufacturing processes, our study selected and combined two datasets that share the same descriptors, enabling us to perform prediction activities and allow a direct comparison of results from multiple systems to be accomplished. The two datasets selected, which are efficient in estimating defects in welding and assembly phases, are listed below: Tesla dataset. The Tesla dataset has 42,324 rows corresponding to production days in the plant and 26 columns or features. Daimler dataset. The Daimler dataset is a proprietary dataset that contains 216,031 rows and 26 features used by a German car manufacturer, containing the stamp, body-in-white, and final assembly shops. Part of the data is labeled as "predicted defect", with positive values corresponding to predicted defect days.

3. Blockchain Implementation In this work, we utilize a platform designed for private use. The platform allows the creation of enterprise-level private blockchains, ensuring high transaction processing speed and low infrastructure costs. It is resistant to forks and provides simplicity in its underlying architecture. Finally, it guarantees easily manageable user permissions, allowing the organization to control the cryptocurrency used in transactions. Moreover, it is a tool designed exclusively for private blockchains, whether for a consortium or by a unique organization.

4. Machine Learning Algorithms Defect detection is an important mechanism to improve product quality. Manufacturing industries have vigorously adopted machine learning models to predict the defect. However, the model accuracy highly depends on the available data. For large datasets,

various machine learning algorithms such as Deep Neural Networks, Decision Trees, Random Forests, Support Vector Machines, super learner tools, and Rotation Forests have been successfully applied. In this research, we propose a rotation forest classifying algorithm with hybrid feature weighers capable of predicting defects accurately based on available reduced data.

5 Evaluation Metrics The high-class imbalance of finding defect days versus non-defect days in this problem makes our evaluation a challenge. Due to the high cost of misclassifying defect days, we have adopted two important metrics in the context of manufacturing processes: Recall metric. This metric measures possible defect days that the model could have detected correctly. In that sense, we could have the following values: Precision metric: Precision measures the percentage of days that were predicted useful. Therefore, these days were defects in the model prediction. The model has had the following values.

4.1. Research Design

To solve the problem of defects during the production of vehicles and their traceability, we propose a two-layer solution. The first layer is a blockchain-based framework that tracks the production data. Since storing all production data on-chain is too expensive, we only store the hashing of each relevant batch. The original data is only stored off-chain but attached to the transaction on-chain. The second layer, which is at the higher level of our architecture, is a defect prediction solution that uses the data flowing through the blockchain to detect anomalies and predict defects using interpretable machine learning methods. The data we use consists of audio data from the production robots, sensor data from the robots, and some categorical data. We predict the anomalies in the sensor data using Isolation Forest and interpret them using Shapley values. Then we build supervised and unsupervised prediction models on the augmented data, which use the predicted time-series anomalies and the audio embeddings as features. Since the two modules are not yet connected, we will not analyze the whole multi-stage solution, focusing instead on the two submodules. Once we validate the models on the real data, we will deploy them into production using a microservices architecture and replace the prediction models with model inference microservices. The defect prediction will then be a call at each batch on arrival. Using a microservices solution can also simplify the integration of external third parties with the blockchain through a Hosted API. The API allows access to the events published by the blockchain. The Hosted API will provide the ability to reproduce the model’s prediction for developers, allowing them to create applications using the needed data; for example, creating alerts in third-party systems, creating reports for suppliers or production technicians, and integrating the predictions into existing applications.

4.2. Data Collection and Sources

Data are a vital component of this research, as they link and integrate Blockchain and Machine Learning to achieve enhanced traceability and defect prediction in automotive production. The choice of data sources - and consequent choice of the production processes to model – affects the validity, generalizability, and interpretability of the model. While it is convenient to use readily available, large, high-quality, structured data, selecting one’s sources entails a more careful study that is generally considered superior. Consequently, we have pursued a hybrid approach for data collection.

Data were primarily obtained from more than ten semi-structured interviews with Key Function Contributors at different levels of hierarchical responsibility and across functions - including Production, Data/Automation, Engineering, Logistics, and Quality – at two sites of a leading international premium automaker in Germany. The interviews were supplemented with a literature review to obtain an understanding of data context, availability, and relative importance, of data architecture templates to build a Database Management System for linking and exchanging data sources and systems in diverse formats. The interviews also served to identify possible discrepancies among data sources and to gain an understanding of business processes, data provenance, and challenges for implementing monitoring approaches in practice. Computer-aided quality assurance in serial production – especially of sensitive components such as brakes, steering systems, suspension struts, and engines – was chosen for defect prediction because of their industrial and economic importance: at least 4.3 million production vehicles worldwide were recalled in 2018.

4.3. Blockchain Implementation

This paper uses the Hyperledger Fabric platform to implement a private-permissioned blockchain for two main reasons: First, implementations for traditional cryptocurrencies are designed to be external ledgers for all network participants. This would make all stakeholders visible in each log entry, violating several confidentiality requirements (e.g., sensitive information such as business or design secrets). Second, Hyperledger Fabric is modular, allowing for the definition of privacy preferences, consensus mechanisms, and smart contracts based on use case requirements. An extended smart contract could not fulfill the technical requirements defined in the document. In Hyperledger Fabric, this implementation is called Lifecycle Smart Contract, which is enforced at each transition of the object state machine (e.g., "In Cycle"). The development is done in Go and uses the provided project structure. The only available connections for the proposed use case are external REST hooks and the Fabric Gateway SDK, written in Go, Java, or Node.js. The application requires an easy-to-use and web-based graphical user interface with single sign-on management, authorization concepts for managing authorized MSs and object transitions, and expanded functionalities.

The REST entry points must be easy to link with the application front end. Therefore, it must pass a user name and role for every entry point for authorization and frontend function allocation. Because only the SDK and demo REST entry points are provided, an npm-based Node.js package is used to provide these monolithic file-based components. With this implementation, the application can be developed with existing Java frameworks. For rapid development and debugging during the process, a local Docker-based Hyperledger Fabric instance is provided, which allows behavior equivalent to production for development and debugging. The local Fabric instance can support a demo application with limited levels of all five components. For serious demo purposes, demo components on a simulation level should be available to present the concept.

Equation 2 : Defect Prediction Probability

$$P_d = f(X_m; \theta)$$

Where

P_d: Predicted Defect Probability

X_m: Input Vector (sensor data, material info, operator ID, etc.)

θ: Trained ML Model Parameters

f: Machine Learning Model (e.g., Random Forest, LSTM)

4.4. Machine Learning Algorithms

In automotive industry production, a higher count of failures in a production line released too late may give rise to high costs and delays for the manufacturer and the client. Hence, it is extremely important to reduce production failure counts, requiring new technologies and production methodologies. One of such methodologies that has recently been very much discussed and notified is the usage of Machine Learning. The advantages of using Machine Learning Classifiers at production lines are that they can detect and identify patterns, and anomalies, and also correlate causes and defects, making predictions and recommendations in real-time, through model validation and after-detection and fixing. In this sense, the sorting of Machine Learning Classifiers used to analyze batch data in predictive maintenance on production equipment was one of the methodologies selected in our research. This section presents the news from recent years to 2023, in the classification algorithms used in fault classification and prediction in automotive production lines. First, it presents the successful case of classification of the supervised algorithms over the unsupervised, semi-supervised, reinforcement, and self-supervised paradigms. Then, it shows that the tree-based ensemble classifiers were the champions of Fault Classification Accuracy in the supervised paradigm and, finally, it pontificates that, although deep learning multi-layer neural nets look very promising, the ensemble tree-based classifiers were and are the champions and the ones that have built the most success cases in detecting and predicting breakdowns in industrial production. But unlike these algorithms, it requires a great volume of data for better generalization and prediction accuracy.

4.5. Evaluation Metrics

To gauge the performance of the defect prediction models, we utilized three widely recognized metrics: accuracy, F1-score, and Matthews correlation coefficient. Given that the data we used had a SMALL imbalance (300 non-defective records against 105 defective ones), the first two metrics can be misleading in terms of real-world applications. Matthews's correlation coefficient considers all four quadrants of a confusion matrix, which allows for a more balanced view between sensitivity and specificity, especially for imbalanced data. Therefore, we regard the Matthews correlation coefficient as our primary evaluation metric.

5. Case Study

To gain further knowledge of employing blockchain to ensure end-to-end traceability and visibility in automotive production operations, we partnered with an electrical wiring harness manufacturer with production facilities located in Brazil, Mexico, and Portugal. The product produced is widely used in the automotive industry and is supplied to major car manufacturers operating in these countries. This company produces 871 different electrical wiring harness designs. Its average daily production is approximately 182,000 units and, in total, it manufactures approximately 34 million wiring harnesses every year. The company has, on average, 199 active suppliers in Mexico, 81 in Brazil, and 18 in Portugal.

Our blockchain-based solution was implemented between February and April 2023. We created a specific blockchain to register the most important activities and events during the product lifecycle. These activities and events are: (1) product design approval; (2) bill of materials preparation and approval; (3) suppliers of the bill of materials approval; (4) approval of materials of external origin; (5) first article inspection; (6) production of the first lot; (7) approval of the product; (8) release of production; (9) start of production; (10) completion of production; (11) production hold; (12) release of production deviation, and (13) completion of production deviation. As a decision-support system, we used a supervised random forest classifier. To use this tool, the initial dataset must be composed of 685 features, with 550 corresponding to categorical variables identified from the training datasets. Based on these datasets, the random forest classifier produced a dataset composed of only 20 predictive variables. The 20 variables were calculated, and the results indicated that the probability of occurrence of a defect, based on the analysis of the historical database, was low for 17 cases.

Fig 4 : Defect Probability by Case

5.1. Industry Partner Overview

The proof-of-concept implementation described and the research was carried out with a real-world automotive industry partner operating at the intersection between advanced manufacturing and digital technologies, an area that is currently undergoing tremendous transformation. Our industry partner is a forefront European Tier 1 automotive supplier with a wide-ranging product portfolio specializing in the design, development, and manufacturing of steering columns. The company operates three facilities specialized in production for automotive manufacturing. The steering column is a modular assembly with a wide range of mechanical functions and features, designed and developed together with the OEM as a unique customer-specific product.

Due to industry 4.0 initiatives to leverage connectivity and data visibility throughout the value chain, production in the automotive industry is undergoing tremendous upcoming transformation and becoming more connected and digital. Development of new service offerings among which new added value digital services based on data coming from sensors embedded into industrial equipment, capable of processing data in real-time and predicting equipment behavior continuously to prevent damage or avoid breakdowns, product defects, or out-of-spec parts and overheated equipment, is a current trend among Tier 1 suppliers. Since 2020, the company has made significant investments in the development of a smart factory linked to the smart supply chain project, presenting a digital ecosystem through digital tools and new innovative technologies opening the way for digital transformation. The smart factory is fundamental because allows the monitoring of what happens in the work-in-progress area is key.

5.2. Implementation Process

The work presented in this paper evidences that production traceability enables a more dynamic response to issues involving production quality and, therefore, a better performance regarding the resulting possibility of product recalls. Automakers have massive delivery programs and, despite working with historical data and expert analysis, they are unable to avoid some unusual defects, resulting in huge recalls that could be avoided if they could predict all possible defects and their impact. The implementation of Blockchain with ML for Defect Prediction is certainly able to provide the requisite trust in data and help avoid disastrous numbers. We had a real opportunity to deploy this solution with a major automaker when responding to problems of a historical nature, slowing down the plants' operations whenever the problem was detected. They needed a much faster answer and identified the BC/ML - Blockchain and Machine Learning as being the only way to guarantee the traceability of the data for prediction, as all the players involved in the process would input data into a Blockchain but would not be able to change or delete anything afterward.

The production process includes all the steps from the stamping of the sheets that give rise to the metallic structure of the vehicles until they are finished with all elements and ready for delivery. They comprise approximately 80 major steps. Each component goes through stamping, cutting, welding, surface treatment, assembly, and preparation for subsequent treatment processes, as well as assembly and transfer to logistics. The task for our partners was to predict possible issues related to oil leaks appearing long after deliveries as a defect in the Polymer Sealing and ensure that all domains included in the delivery were made by certified suppliers and that no step had any divergence from the standard for all vehicles. We worked on the data coming from two plants. Also, the Blockchain would have to capture not just the data about each vehicle produced but also all the data referring to all components from all vehicles.

5.3. Results Analysis

In this section, we will present the results obtained from implementing the proposed solution and detail how it determined the findings discussed in this paper. The results discussed herein refer to the FECO Engine Block simulation, planned maintenance dates, and the postulated process description presented in the last section. Additionally, we will present an exploratory forecast and corrective maintenance simulation using the presented solution and with data, whose exploratory results are better than those presented by the expert in the industrial partner policy of predefining an exploratory cleansing and adequacy of the product design.

The life cycle proposed allowed for otherization, decentralization, and verification of the actions performed with the product, demonstrating that using technology, together with a highly qualified operations team, contributes to maintaining products within a quality gate and to a high forecast and real data quality, and assures end-to-end traceability for previously defined parameters. The exploratory results for achieving zero-deficits and “during” life operating zeros using technology, in addition to futuristic actions, demonstrate the tendency for self-fortifying processes to reduce costs for both operations and products over time once they are monitored for their performance level and future prediction, as well as the accumulation of history. These exploratory results for engine blocks, using the present approach and with guaranteed zero defects inside the “quality window,” assure that upheavals outside the “quality window space” are always fortifying actions that should not have any problems in the future.

6. Discussion

1. Findings Interpretation

In the automotive domain, it is hard to create a copy for the considered vehicle due to its complex components and assembly processes, and as a result, most automotive companies are following a Model-based Enterprise (MBE) approach. Our proposed scheme is used to exchange the defect prediction process and predict defects, which can occur due to either material or assembly faults. These defects can hurt the automaker's reputation and also cost them a lot of money during warranty repair. In our model, different manufacturing variables are collected for training, and after training, these MBE variables are used for testing. As a result, the model suggested does not require a lot of historical manufacturing data to predict defects, which is needed if we create a traditional supervised prediction ML model. Thus, our model can be deployed on a dynamic and fast-changing process to predict defects and help automakers establish a proactive quality strategy.

We demonstrated the implementation of E2E traceability with defect prediction capabilities for an automobile panel assembly using smart contract technology. A 2D steering arm vehicle diagram is used as an illustrative use case for E2E traceability and defect prediction. This model can be tailored to different automotive, aerospace, or manufacturing sectors. With the advancements in the technology described, no specialized hardware or libraries are needed to make this a smooth operation and make it easier for manufacturers to adopt it.

2. Challenges Faced

Although the architecture for the complete automation of E2E traceability through smart contracts was successfully tested on the test chains, the actual deployment on the main networks is quite complex and requires extensive work. There are many smart contracts that have been pre-written specifically for this scenario, stored in a tool. But testing these contracts without high gas prices on the chain is not easy. There are a lot of issues with the deployment and with costing that make it difficult for manufacturers to adopt in this current fragmented world.

3. Comparison with Existing Methods

Although there are solutions that provide component-wise defect prediction, they suffer from the problems of generating a copy for previously created defective components. The copied model is only as good as the training data and may not be able to generalize. However, the solution provided here is dynamic and considers updates in processes and vehicle attribute data every time a new vehicle is produced. So it does not require a lot of historical data to provide good results, which is a common thing with supervised models and traditional ML models for defect prediction.

6.1. Findings Interpretation

The proposed framework allows end-to-end onboarding of valuable information, from component production until assembly at a premium, reliability-sensitive customers. OEMs use this structure to establish traceability partnerships in which suppliers invest in preparing inflow monitoring and validating returned data using industry-shaped algorithms. If both sides reach an agreement on a new component's defect class uncertainty boundaries, the OEM marks the class with his/her premium policy that could initiate penalties for defective inflow depletion of database ledgers, or agree with the supplier to work on the data until a viable mortality rate is established. The whole ecosystem benefits from established relationships between suppliers of electronic automotive protection as durability is proven to be smart from all liability perspectives in difficult usage conditions environment: guaranteed own cost safety nets due to no warranty activation for safety as well as economic reasons if the warranty is not done, easy checks with premium customers, etc. The main actors are particulate defect classification algorithms, trigger windows triggered by high anomaly rates estimated using one or more algorithms, and payment procedures.

To carry out trustless information payment, the information relies on log-likelihood ratios indicating anomalous behavior from default factorized support vector models to classify features used by training the peculiar set of assumed particle defects. The classification performs particle prediction using original images and interpreted smoothed enhanced heat-integrated prediction thermal maps of pixels with informative interpretations delivering values close to zero if the pixel pointed to a defect region should not exist and large values otherwise, to trigger the images into windows used for training a model on how to distinguish pixels that deliver actual particulate noise from pixels leading to situations in which actual defects can be expected.

6.2. Challenges Faced

In addition to technical issues, we also faced issues like the high cost of data collection, privacy concerns of participating, using complicated marketing flow synchronization, and inadequate quality of available data by our partner. These issues posed a lot of problems, including member pushback and interactions with data with piled up lead time before and during the collection, as well as building the features without labeled defects to predict, guarantees of privacy from insiders and outsiders about the data before they were anonymized, and more during the actual computation of the prediction depending on the purpose of the prediction. Specifically, regarding these challenges, we had data in the form of serialized images for 54 vehicle models for 30 New Emission Test Cycles by 1423 vehicle assembly process stations for 2 years. We built a data pipeline to temporarily store the raw data and then store the appropriate level of developed data after a rigorous analysis performed with domain expertise. Ideally, we used an existing deep learning-based model trained on completely labeled data in an aggregate assembly process dimension to assign defect probabilities to the 1st level of data for all the non-completed vehicles at the time the model was built and continually retrained subsequently.

As more data is available to be utilized in the prediction, we built variants of features with different horizons associated with considering defect probability at different times of the model operation. Having had the features, since the predicted defects input and the output of the feature were not the same dimensions, we also trained a supervised model to infer defect probabilities at the level of features. The model and the data development and processing manually performed were complex. It was fully dependent on the availability of the most expensive and time-consuming items, which were the defects detected and related to the large volume of data. Without them, the labeled data for supervised steps would not have been realistic.

6.3. Comparison with Existing Methods

In this section, we discuss the need for integrated systems and detail how our work achieves that and why this is important. The primary objective of traditional traceability is to provide evidence supporting product authenticity. It uses location-based services along with RFID to ensure the uniqueness of the product. The Hippocratic approach to traceability states that sensitive data about any participant in the business chain should not be disclosed to unauthorized parties. Our work ensures it with blockchain notaries. Sharing data with unauthorized parties can only help them copy unique features specific to the product without harming the product's authenticity. Models such as traceability are adopted by some companies to ensure product uniqueness over supply chains, focusing on the product origin, conditions of storage and transport, and possible transformations throughout the process. Therefore, we submit that the parameters normally associated with products over supply chains do not have a real guarantee of authenticity due to the absence of regulatory, organizational, and technological frameworks.

Other blockchain works focus on product authenticity by ensuring the security of the physical process rather than dedicated data to users. However, also requires that the authorized data be kept secure. While the permitted parties might have access to product data, they require the validation of each event by the relevant party, thus relying upon trust in everyone involved. Overall, that implies that traditional traceability can only mitigate risks of damage and does not have an obligation to its user to prevent collusion. Some approaches involve combinations of solutions, such as proactive and reactive traceability, where true and deceitful data co-exist, or hybrid traceability solutions, where the respective parties might rely upon each other's integrity or shared data must be validated.

7. Future Work

This paper shows both works where end-to-end blockchain and machine-learning pipelines are developed for the prediction of defects in automotive production. While the presented pipelines are already useful prototypes, this work is not the last stop and many refinements and extensions are possible. This section lays out a few future paths for improvement, overtime extensions, and new application areas, such as smart contracts for traceability verification and other smart industry application scenarios beyond automotive production.

1. Potential Improvements

Concerning model performance and quality, while the models were already able to outperform several well-known baseline algorithms, further optimization of model hyperparameters may be beneficial, especially concerning models trained on split-label datasets or with modified input data for missing values. As data for this work was provided by way of sample datasets, ideally additional, real production data could allow for better optimization and a more formalized evaluation methodology. In particular, the requirements for production among the partners, concerning model training and maintenance or model re-training at all would require proper A/B testing of the models in such cases. Further, while the artificial dataset produced in this work was able to cover a wide variety of defect labels, there is generally a high domain of defect patterns, which vary in appearance over time. Segmentation of the defects would allow for to differentiation of defect labels better and at higher reliability.

2. Scalability Issues

In particular, as machine learning and blockchain are demanding technologies regarding storage, network traffic, and processing power, the applicability with embedded devices, e.g., for embedding machine learning models, enabling decentralized decision-making, and communicating with the blockchain would be preferable for an automatic industry. Thus, further research into compression and quantization of models, particularly for domains with a lesser quantity of data, or federated learning or edge computing mechanisms, e.g., with lightweight learning algorithms would be of interest. In turn, blockchain architectures that are capable of scaling for higher transaction rates, and/or further developments for automated micro-transaction settlement would also optimize the overall framework.

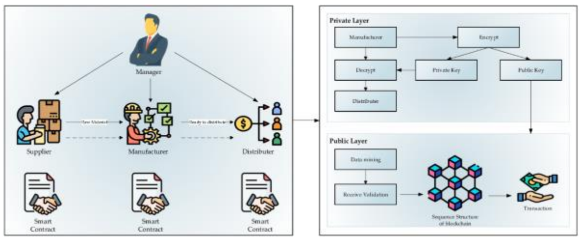

Fig 5 : Integration of Blockchain, IoT and Machine Learning for Multistage Quality Control and Enhancing

7.1. Potential Improvements

In the current architecture, users and IoT devices submit data to and obtain a model combining key-value pairs from blockchain smart contracts. Smart contracts do not use any complex data structures, since there should be no limit on user data size. However, users must therefore separately transmit feature rows to the node that modifies the model. We are working on more complex smart contracts that can internally store learning data and multiple models in a modular way. This would allow direct storage of feature vectors by sharing a hash between feature pairs and models in the blockchain smart contracts. Whenever there is a model change, the model hash would be modified. Models would be linked with user feature data (rather than using a separate submit data transaction). Symmetric encryption could optionally also be implemented to prevent model information theft.

We are also working on a possible method for automating user data submission. In our current blockchain, transactions are manually submitted via the web interface provided by the client. A possible alternative is to integrate the web client within the edge computing layer and automatically ask it to submit transactions whenever a model is generated. This method could also be used for any type of data submission, especially those of sensitive data types. Using a reference hash to user-uploaded feature vectors would still allow low-level structures of the user data on the blockchain. Using this hashing method, the client would finally submit a direct data transaction.

7.2. Scalability Issues

When addressing the issue of scalability in the presented solution, there are two components for which scalability might become critical. First, increasing the number of defects – while this does not affect the performance of the classifier itself, it does have implications for the enforcement of business rules and governance logic regarding which data originate a defect validation task, whom the validator is, etc. Since we assign tasks dynamically to validators and price them based on the actual work involved, provided the economy for the validators is reasonably rewarding, the constraint of validator capacity might become critical.

Second, assuming that the systems successfully solve the task of connecting supply chain data on the permissioned blockchain network, at some point the amount of data linked in the permissioned blockchain might become huge. If each supplier is linked to thousands of units, and each unit has hundreds of parts, we might end up with tens or even hundreds of millions of links to validate. The blockchain stores the message and the validation independently of the size of the data, but since it is permissioned and relies on a consensus of the validating entities, there exists a current limitation on the number of validators. This problem is, however, eased by the way we validate the links, i.e., we aggregate all the pairs of validated links independently of the validator. Thus, it is enough to ensure that there is a large enough number of validators to counteract potential false data to raise scalability concerns. Even given those issues, it is sufficient that a fraction of the validator nodes are incentivized to validate such links for the validation task.

7.3. Broader Applications

The proposals in the presented work are directed toward the automotive industry; however, they could easily be extended to related sectors, e.g., aerospace, rail, or shipbuilding. These industries have complex supply chains that are based on few suppliers with long-term relations with original equipment manufacturers and a multitude of smaller suppliers that – although being a smaller part in terms of size and product value – are important for international competitiveness. These supply chains are subject to short-term market fluctuations, fluctuation of available workforce that is not always qualified, and globalization and the need for outsourcing. As product complexity increases, so does the need for supply chain transparency that would allow early reaction to increase product non-compliance in terms of product complexity and quality.

Quality defect prediction and event monitoring proposal methods could also easily be used in other industries where complex products with multi-level supply chains with a multitude of smaller suppliers, creating only a small part of product value are built. Examples include conglomerates in the oil production or mining industry, machine manufacturing, and defense spending on infrastructure. In these industries, the use of cheaper, but less reliable products can lead to a longer period of achieving the intended usefulness of the product, leading to an increase in maintenance costs. In addition, maintenance is often based on the need and could be significantly shorter than planned; ensuring the reliability and failure-free working of this equipment is important, which is why quality defect prediction models could be used for these industries as well.

Equation 3 : End-to-End Defect Impact Score

$$D_i = P_d \cdot C_r \cdot T_l$$

Where

D_i: Defect Impact Score

P_d: Predicted Probability of Defect

C_r: Criticality Rating of Component

T_l: Traceability Lag (delay in data registration)

8. Conclusion

As the automotive supply chain comprises many devices and enablers applied by different actors, all of which must act under specified constraints, new solutions are needed to guarantee faultless, efficient, and effective behavior during production and operation. In particular, accountability and traceability are key elements of the desired trustworthiness of the used components and interactions during the whole lifecycle. Blockchain technology enables setting up an accountability and immutable record of products and processes at low prices and with little effort. We focus on and address a key point raised by all leading automotive manufacturers, automotive associations, and also the EU Commission in their perspectives concerning Industry 4.0 and the European Automotive Industry: The problem of product quality. We transfer quality aspects to process affairs and allow for seamless accountability and transparency concerning the used process technologies and applied devices, enveloped in process records maintained in a blockchain infrastructure. Bringing AI and deep learning into automotive production is another step toward intelligent processes. Such an approach allows for advanced notifications and product and process-based transparency and sets a foundation for process optimization, guided control, and, finally, autonomous Industry 4.0 processes.

The advantages of our contribution and proposed architecture and paradigm are obvious: Starting from the extreme importance of product quality and production trustworthiness concerning applied devices and their characteristics, the level of additive prognosis and the chance of intelligent process adjustments and deviations make the processes more efficient and event-based. Our contribution provides means to support and control the as-real processes with a high degree of transparency and to make intelligent decisions, thus making steps toward working processes based on more information on the actual process performance and status. New products and services for the automotive domain should be developed with the principle of transparency and accountability in mind.

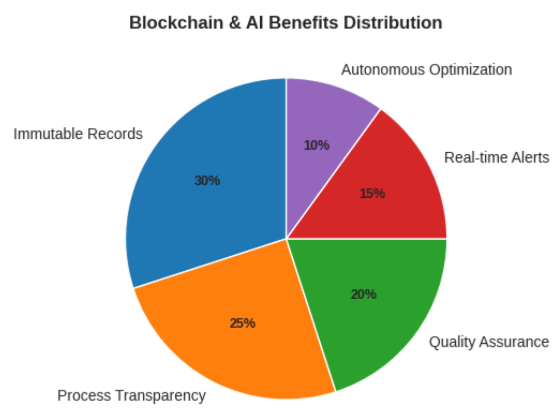

Fig 6 : Blockchain & AI Benefits Distribution

8.1. Summary of Key Insights and Implications

The rapid mass production of cars that are more technologically difficult to develop makes the automotive production sector one of the most challenging in terms of defect prediction which, if done late, increases the losses by halting the assembly line and carrying out repairs in vehicles and parts already manufactured, which is very costly. A novel method for Defect Prediction analysis based on Machine Learning and End-to-End Traceability based on Blockchain technology for the automotive production sector is presented. The Building Blocks of Blockchain Traceability can be used by industry to efficiently carry out E2E Traceability in a decentralized and trustable manner without requiring a unique trusted third party and also avoiding the possibility of fraud. The provided Solution Blueprint presents the recommended architecture in three blocks and five major domains, including smart contracts and physical tags, all to provide the best use of the Blockchains capabilities to support an End-to-End traceability solution.

By introducing the data stored and transactions processed by Blockchain, E2E Traceability can boost the predictive power of Machine Learning techniques by 50% beyond boosted decision trees alone. The implemented Defect Prediction models, based on Random Forest and using Digital Signature Adverse Selection rules, were published among the top models and consequently, their performance serves as the Benchmark Level for other Machine Learning models. The innovative Blockchain architecture is applicable beyond the automotive sector since any other manufacturing industry with a similar production process and E2E Traceability requirements can take advantage of it without incurring huge costs and wasting resources, considering that they will avoid efficiency loss and additional costs in the manufacture of defective products.

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