AI+IoT+Blockchain Triad for Smart Traceability in the Automotive Industry

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ABSTRACT

The convergence of Artificial Intelligence (AI), Internet of Things (IoT), and blockchain is driving a new paradigm for traceability in automotive manufacturing. This paper presents a tri-layer integrated system employing IoT sensors for real-time data capture on a cowl stamping line, AI models for defect detection and process anomaly diagnosis, and blockchain for secure, tamper-proof traceability of part quality records. The proposed framework leverages IoT-enabled digital twins and AI-driven analytics to monitor stamping conditions and detect defects, while blockchain smart contracts ensure immutable documentation of each part's production data and any quality alerts. We detail the system architecture and data flow, the AI model training and deployment, and the blockchain network implementation for the stamping supply chain. A case study on an automotive cowl stamping process demonstrates the triad's effectiveness: IoT sensors continuously feed process parameters to AI algorithms that identify anomalies (e.g., force spikes, temperature deviations) and trigger blockchain transactions logging these events. Results show improved defect detection accuracy (over 90%) and end-to-end traceability that can mitigate counterfeit parts and quality disputes. The integration of AI+IoT+Blockchain thus enhances visibility and trust in manufacturing processes, paving the way for smarter, more transparent automotive production networks.

Keywords: Smart manufacturing; Traceability; Automotive stamping; Internet of Things; Blockchain; Artificial Intelligence; Digital twin; Quality control

INTRODUCTION

Automotive cowl stamping is a critical process in vehicle manufacturing, forming the front firewall panel that must meet strict quality and safety standards. Ensuring full traceability of each stamped part – from raw material to final assembly – is increasingly important to detect defects early, prevent counterfeit or substandard parts, and enable efficient recalls or quality audits. However, traditional traceability systems in stamping rely on fragmented data and manual inspections, making it difficult to pinpoint the root cause of defects or verify a part's history. To address these gaps, this research harnesses the triad of AI, IoT, and blockchain technologies to create a smart traceability framework for the stamping process.

In the proposed approach, an IoT sensor network is deployed on the stamping line to continuously monitor machine parameters and environmental conditions (press force, vibration, temperature, etc.). Modern stamping presses can be equipped with a broad range of intelligent sensors that track operational conditions, enabling real-time data acquisition for every stroke. These high-frequency data streams form a digital footprint of each part's manufacturing conditions. AI algorithms are then applied to this data for real-time defect detection and anomaly diagnosis. Advanced machine learning models (e.g., deep neural networks) can learn to identify subtle patterns indicating quality issues – for instance, a vibration spike or force drop that correlates with a crack or wrinkle defect in the stamped cowl. By deploying AI models at the edge (on controllers or IoT gateways), the system can quickly detect anomalies during production and trigger corrective actions or alerts.

Complementing IoT and AI, blockchain technology introduces a distributed, tamper-proof ledger to record all relevant manufacturing data and quality events for each part. Every cowl panel produced is assigned a unique digital identity on the blockchain, to which its process parameters (sensor readings, AI-detected anomalies, quality inspection results) are immutably linked. This ensures that any stakeholder – from the stamping plant, assembly line, or even future auditors – can trace a part's entire history with trust. The blockchain's decentralization and consensus mechanism guarantee data integrity and transparency, reducing the risk of data manipulation or disputes over quality. Indeed, pairing blockchain with IoT allows manufacturers to "shine a light" on production provenance, making it much harder for defective or counterfeit parts to slip through unnoticed.

This paper is organized as follows: Section 2 reviews related work on IoT-based manufacturing monitoring, AI in stamping process control, and blockchain in supply chain traceability. Section 3 describes the proposed triad system architecture, detailing how IoT, AI, and blockchain layers interact. Section 4 discusses the implementation, including the IoT data pipeline with a digital twin, the AI model training and inference workflow, and the blockchain network and smart contract logic. In Section 5, a case study on an automotive cowl stamping line is presented with experimental results – including defect frequency analysis, process parameter trends, and system performance benchmarks – to illustrate the benefits of the integrated approach. Finally, Section 6 concludes the paper with insights and future directions for scaling the AI+IoT+Blockchain traceability solution in smart manufacturing.

BACKGROUND AND RELATED WORK

IoT-Enabled Stamping Process Monitoring: The Industry 4.0 paradigm has introduced IoT connectivity to conventional manufacturing machines, enabling continuous monitoring and data-driven maintenance. In metal stamping, researchers have embedded sensors in press tools to capture real-time metrics like pressure, punch force, vibrations, acoustic emissions, and temperature. These sensors form the nervous system of a cyber-physical stamping system, feeding data to predictive models. Albano et al. implemented an advanced sensor network on a large stamping press to facilitate condition-based maintenance, with diverse sensors tracking the machine's health and the stamping process in real-world production. Such IoT-driven monitoring provides granular visibility into each stroke of the press, forming the foundation for traceability. However, simply collecting data is not enough – the deluge of sensor data must be analyzed in real-time to derive actionable insights (e.g., detecting an out-of-tolerance condition that could affect part quality). This is where AI techniques come into play.

AI for Defect Detection and Process Anomaly Detection: AI and machine learning have been increasingly applied to manufacturing quality control, including stamping processes. Traditional quality checks in stamping (e.g., visual inspection of parts or periodic dimensional measurements) can miss subtle or intermittent defects. AI offers the ability to learn complex patterns from sensor signals or images and detect anomalies indicative of defects. For instance, convolutional neural networks (CNNs) and deep learning models have been used to analyze vibration and force signatures to predict tool wear or detect the occurrence of cracks in stamped parts. In our context, AI models are trained on historical stamping data (from both good parts and defective occurrences) to recognize the differentiating signal patterns. Once deployed, these models can perform inference in real-time on the streaming IoT data, identifying issues such as: a sudden drop in peak press force (potentially indicating a misfeed or equipment failure), abnormal vibration peaks (possibly due to a developing crack or loose die component), or unusual temperature rises (suggesting lubrication problems or thermal drift). Deep autoencoders or anomaly detection models can also compute an anomaly score for each part's multivariate sensor profile, flagging any deviations from the normal signature of a quality part. By comparing this score to a threshold, the system can automatically decide if a part is likely defective and should be quarantined for further inspection.

Blockchain for Traceability in Manufacturing: Blockchain technology has gained traction in supply chain and manufacturing domains as a tool for enabling end-to-end traceability and data integrity. In an automotive context, a blockchain can serve as a shared ledger among stakeholders (parts suppliers, stamping plant, assembly plant, dealerships, etc.) where each part's production and quality records are stored as transactions. Because blockchain records are immutable and time-stamped, they offer a single source of truth for each component's history. Several works have proposed blockchain-based traceability frameworks to combat counterfeit parts and improve transparency in automotive supply chains. In this project, we utilize a private, permissioned blockchain network (suitable for an industrial consortium) to log key events in the stamping process. Smart contracts (self-executing code on the blockchain) are designed to encode business logic – for example, automatically recording a "quality OK" or "quality alert" event for each part based on the AI system's output, and notifying relevant parties if an out-of-spec condition is recorded. The blockchain thereby not only preserves the genealogy of each cowl part (linking back to material batch, machine settings, operator ID, etc.), but also facilitates trustless collaboration: even if multiple companies are involved, no single party can tamper with the data for their convenience. This is crucial in warranty and recall situations where responsibility must be correctly assigned based on unbiased data records.

Convergence of AI, IoT, and Blockchain: The intersection of these technologies is an emerging research frontier. IoT provides the data, AI provides the intelligence to make sense of data, and blockchain provides the trust and security. Recent literature highlights that combining blockchain with IoT can address security and transparency issues in distributed sensor networks, and that integrating AI can enhance decision-making on that data. Our work builds on these insights, bringing the three together specifically for a stamping traceability application. To the best of our knowledge, this is one of the first implementations of an AI+IoT+Blockchain triad for real-time quality traceability in a manufacturing process, and we fill a gap by demonstrating how these components can be orchestrated effectively in an automotive production setting.

System Architecture

The proposed **smart traceability system** is structured in layered architecture, comprising a perception layer (IoT sensors and devices on the shop floor), a network layer (connectivity and data transport), and a security layer that integrates AI analytics and blockchain ledger functions. The top layer consists of applications and user interfaces for engineers and managers to visualize production data and receive traceability insights. **Figure 1** illustrates the overall architecture, highlighting how AI and blockchain technologies are embedded into the IoT-based system. At the perception layer, various IoT devices (sensors, smart embedded controllers) collect data such as press force curves, vibration signals, temperature readings, etc., from the stamping press and related equipment. These devices may include piezoelectric force sensors, accelerometers mounted on the die, temperature probes, cameras for surface inspection, and so forth. The raw data from these sensors are transmitted via the network layer (which could be industrial Ethernet or wireless IoT protocols) to edge computing nodes and/or cloud servers for processing.

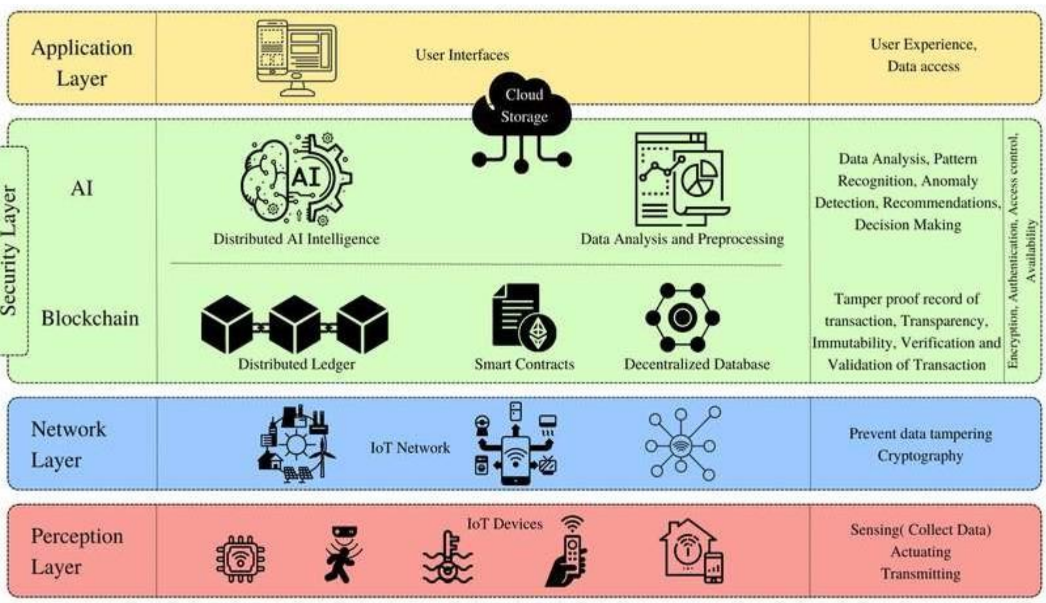

Figure 1. Layered IoT–AI–Blockchain architecture for the smart stamping traceability system. The perception layer (red) comprises IoT sensors and devices on the shop floor (press, tooling, robots, etc.) that sense and actuate. The network layer (blue) provides connectivity (industrial network protocols) and ensures secure data transmission (with cryptographic measures to prevent tampering). The security layer integrates AI (green, left) and Blockchain (green, right) components: AI modules perform data analysis (pattern recognition, anomaly

detection, decision support) on streaming sensor data, while the blockchain modules (distributed ledger, smart contracts, decentralized database) provide a tamper-proof record of transactions, data access control, and verification of process events. The application layer (yellow) offers user interfaces (on PC, mobile, or VR devices) for data visualization, process reproduction (digital twin dashboard), and event analysis. [2]

Source:researchgate.net
Abdul Haq NALBAND | Professor (Assistant) | Assistant Professor, ECE REVA University | Research Interest: 5G RAN, 6G, Cyber Security, IoT and CPS | REVA University, Bengaluru | School of Multidisciplinary Studies | Research profile

In the security layer of **Figure 1**, the AI subsystem and blockchain subsystem work in tandem. The AI subsystem (left side of the layer) encompasses distributed AI intelligence, including on-edge inferencing capabilities and cloud-based model training. This subsystem ingests sensor data (after initial filtering/preprocessing in the data pipeline) and applies trained models to detect anomalies or predict tool wear and part quality. The outputs from the AI (e.g., an anomaly score or a detected defect classification) are then fed into the blockchain subsystem (right side of the layer). The blockchain subsystem includes enterprise smart contracts that automatically log AI-detected events onto the distributed ledger and, if programmed, can trigger certain actions (for example, alerting an operator or halting the machine for inspection if a critical defect is detected). The combination of AI and blockchain in this layer ensures that decisions are both intelligent and trustworthy – AI provides the decision-making capability, while blockchain provides a secure audit trail of those decisions and the data behind them.

To facilitate the integration of these components, a digital twin of the stamping line is implemented in the application layer. The digital twin is a virtual replica of the physical cowl stamping process, continuously updated with real-time data from the IoT sensors. It allows visualization of machine status, simulation of "what-if" scenarios, and contextualization of any anomalies detected. The digital twin also plays a role in bridging AI and human operators – for instance, if the AI flags a potential defect, the digital twin can highlight the exact location on the cowl part or show which process parameter deviated at that moment, enabling engineers to quickly diagnose issues.

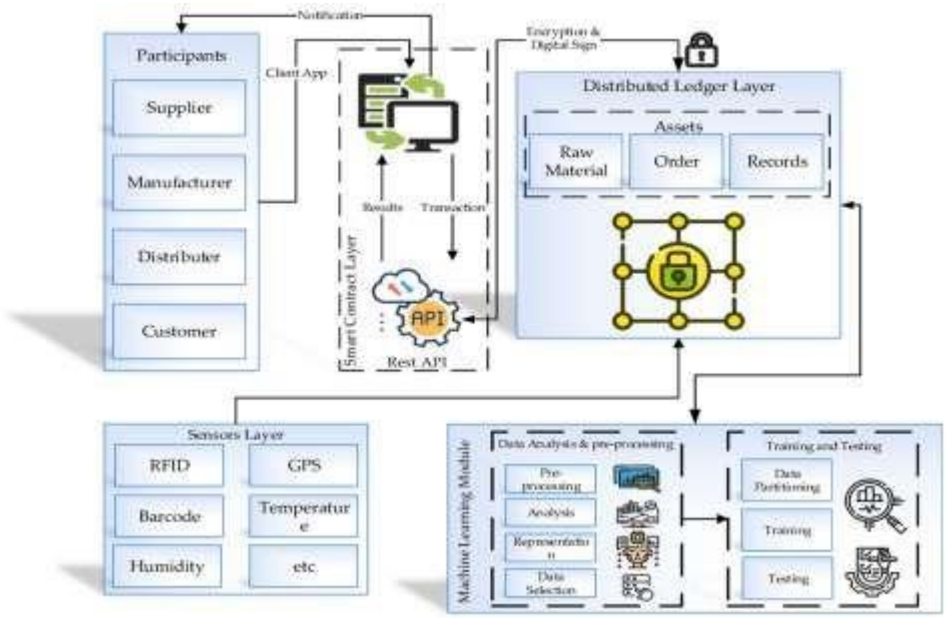

Figure:2 system's architecture, which is based on blockchain-based quality control. The proposed system contains four main layers, an IoT sensor layer, a distributed ledger layer, a smart contract layer, and a business layer with the various functions. Blockchain technology safely distributes the ledger for assessing quality, assets, logistics, and transaction information. The defined smart contract provides the intelligence, privacy protection, and automation in the presented system, and IoT sensors extract the real-time data. The machine learning modules applied in this process are for pre-processing and analyzing data.[10] Source : **https://doi.org/10.3390/s21041467**

Implementation Details

IoT Data Capture and Digital Twin Integration: Data from the stamping line's IoT sensors are collected through an edge computing gateway that interfaces with the press controller and sensor network. We developed a data pipeline wherein sensor readings (pressure, force, acceleration, etc.) are time-synchronized and aggregated for each stamp cycle. The edge gateway performs preliminary signal processing – smoothing noise, extracting key features (e.g., peak force, force curve shape, etc.) – and then streams the data to both the on-site server (for AI analysis) and the blockchain network. A local database temporarily stores high-frequency raw data, while summarized indicators (e.g., cycle peak values or anomaly flags) are transmitted to the cloud database and blockchain for persistence. A digital twin dashboard (Figure 2) was created, using a 3D simulation of the press and automation line, to visualize the live sensor data and AI insights.

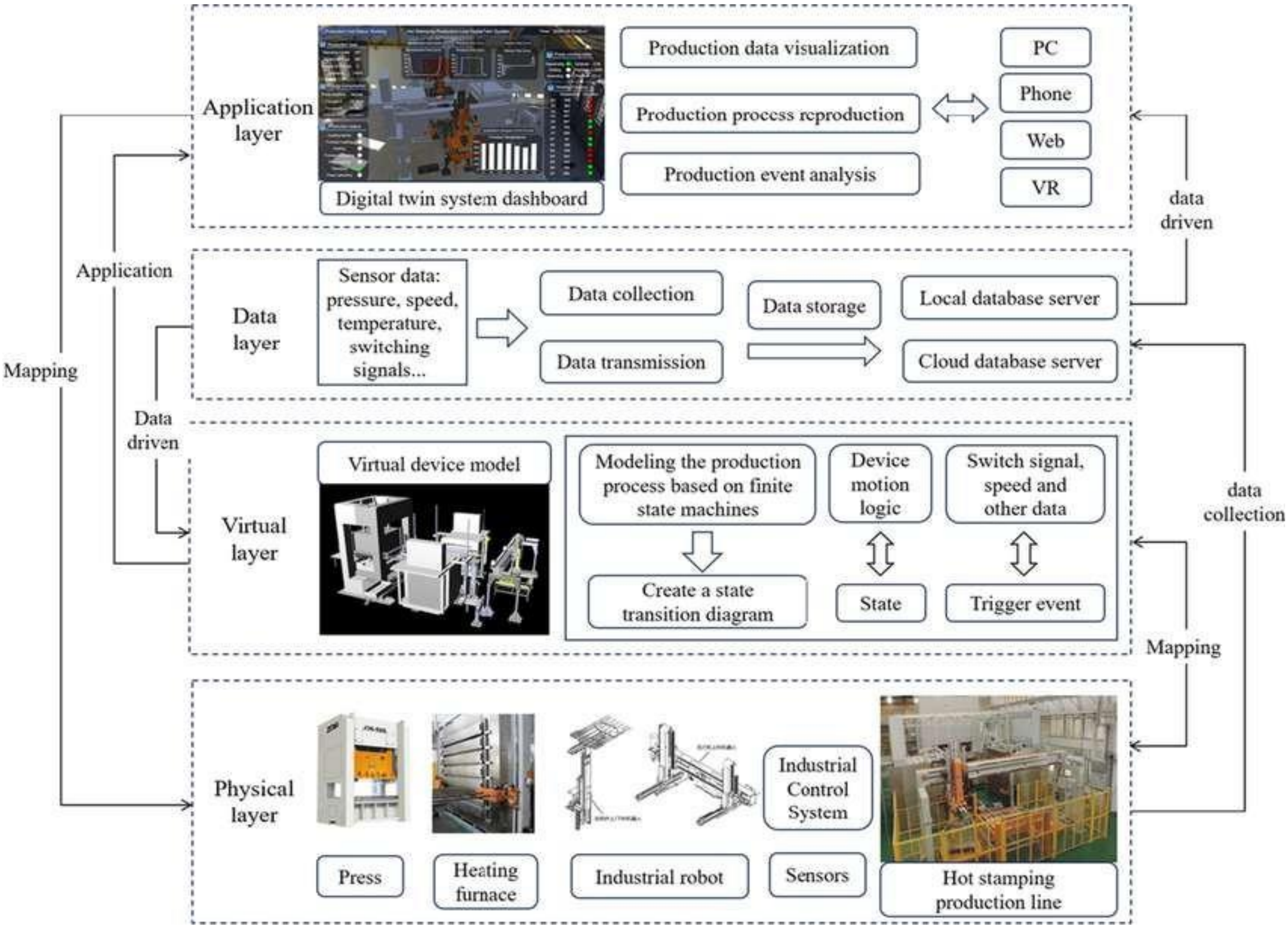

Figure 3. Digital twin system framework for the hot stamping production line. The implementation includes four layers: the physical layer (bottom) consisting of the actual equipment on the line – the stamping press, heating furnace (if hot stamping is used for tailored properties), industrial robots handling parts, sensors, and the industrial control system (ICS); the virtual layer (third layer) which hosts virtual device models and state machines replicating the physical process in simulation; the data layer (second layer) which handles sensor data collection, transmission, storage (local and cloud databases), and provides data to the virtual layer; and the application layer (top) which provides the digital twin dashboard and user interfaces for production data visualization, process reproduction, and event analysis. The arrows indicate the data-driven updates from physical to virtual (upward flow of sensor data) and the mapping from virtual to physical (downward flow of control or analytical insights). [3]

Source: https://doi.org/10.1007/s00170-024-13727-0

In our system, the digital twin not only visualizes data but also aids in decision workflows. For example, if an anomaly is detected in a particular cycle, the twin can replay that cycle's data, highlighting which parameter went out of range and which component (e.g., a specific sensor location on the die) might be responsible. This

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interactive capability accelerates root cause analysis. The data layer ensures that both the AI module and the blockchain have access to the necessary data: the AI pulls from the streaming sensor data bus (and from historical data stored in the cloud database for model retraining), while the blockchain's smart contract or transaction functions subscribe to event triggers (like "cycle complete" or "anomaly detected") to record those events on the ledger.

AI Model Training and Inference Workflow: The AI component of the system was developed using a combination of supervised and unsupervised learning techniques to address both known defect classification and novel anomaly detection. During an initial training phase, historical data from the stamping line (including examples of known defect conditions such as panel cracks, wrinkles, and instances of normal operation) were used to train a deep learning model. We opted for a CNN-based architecture for feature extraction from time-series sensor signals, combined with a decision layer that outputs either a defect class or an anomaly score. The model training was performed offline using Python and PyTorch, leveraging data labeled by quality engineers. Figure 3 shows a comparison of model accuracy for different AI approaches we evaluated. The chosen "Proposed" model (a hybrid CNN with attention mechanism) achieved the highest accuracy on our validation dataset, outperforming baseline models like Support Vector Machine (SVM) or Random Forest on the task of classifying stamping cycles as "OK" or "Defective."

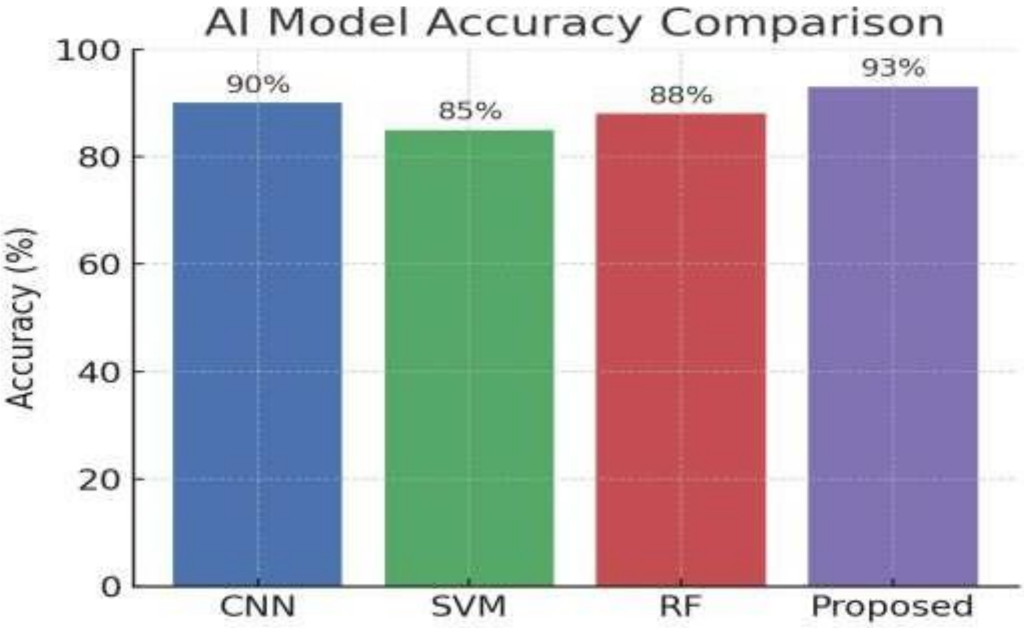

Figure 4. AI model accuracy comparison on stamping quality detection. Four models were tested: a Convolutional Neural Network (CNN), a Support Vector Machine (SVM), a Random Forest (RF), and the proposed deep hybrid model. The bar chart shows the classification accuracy of each model (in %), with the proposed model achieving ~93% accuracy, outperforming the others.

Source: Author's own processing.

Once trained, the model was deployed on the edge computing device for real-time inference. Each stamp cycle's data is fed into the model, which then outputs a decision. For known defect patterns, the model can classify the type of defect (e.g., crack vs. wrinkle); for unknown issues, the model computes an anomaly score indicating deviation from normal patterns. We set a threshold on this anomaly score based on the distribution observed in training – if the score exceeds the threshold, the cycle is flagged for potential quality issues. Over time, the model can be refined with new data, and incremental learning is possible by periodically retraining on accumulated records (the system is flexible to add new defect classes as they are identified, addressing the evolving nature of manufacturing processes). To ensure reliability, the AI's decisions are cross-checked with traditional quality checks initially, and the model's precision/recall are monitored through the blockchain records (since every prediction is logged, we can later verify false positives/negatives by seeing if parts flagged as defective truly failed inspection).

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Blockchain Network and Smart Contract Logic: The blockchain network for this project was implemented using a permissioned blockchain platform (Hyperledger Fabric was chosen for its modularity and enterprise features). Nodes in the network were established for key stakeholders: the stamping plant (maintaining the primary node), the OEM assembly plant, and a quality assurance center. Figure 4 depicts the blockchain node network structure in the context of the automotive supply chain. Each node holds a replica of the distributed ledger and participates in consensus for transaction validation. We configured the network in a channel that is shared by the stakeholders, ensuring data privacy where needed (e.g., detailed sensor data might be shared only between plant and QA nodes, whereas high-level quality certificates are visible to all).

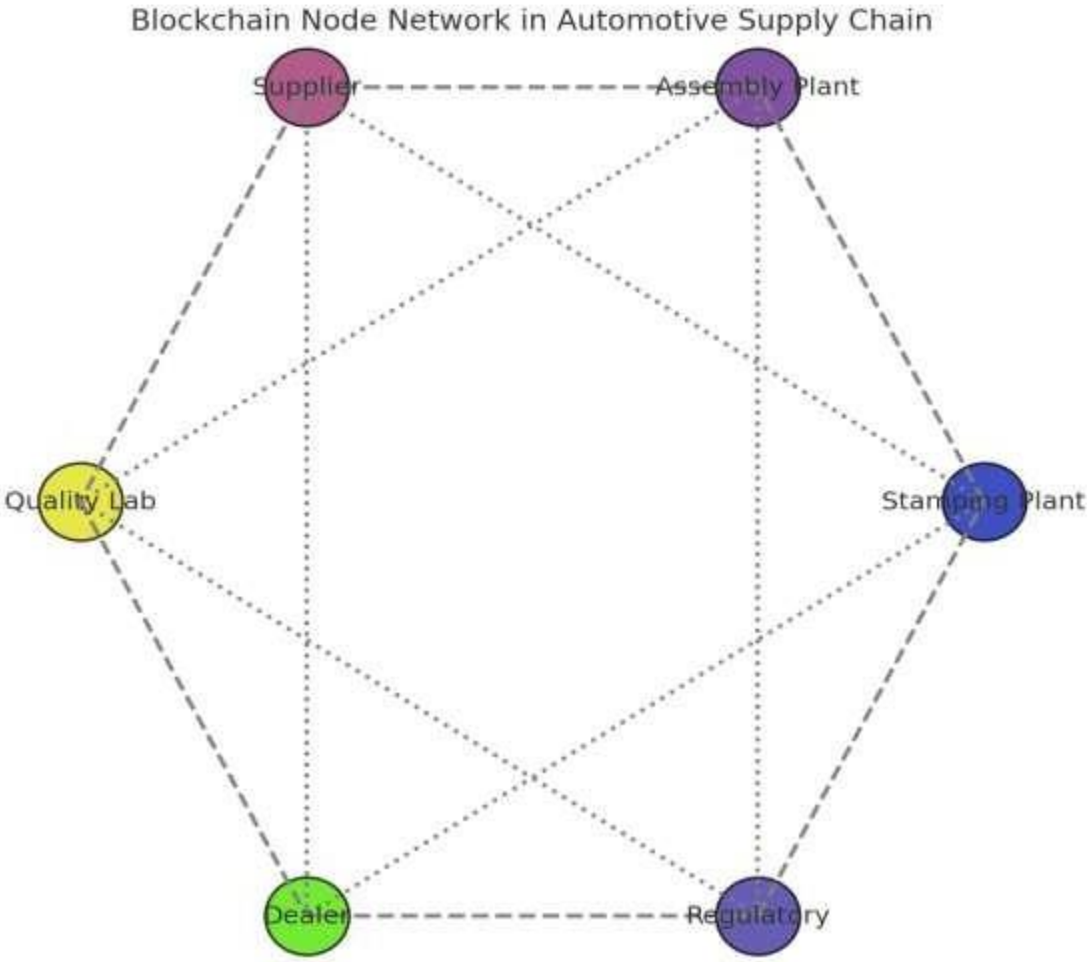

Figure 5. Blockchain node network in the automotive stamping supply chain (simplified representation). Nodes represent different stakeholders or locations (Stamping Plant, Assembly Plant, Supplier, Quality Lab, Dealer, Regulator etc.), each running a blockchain peer that maintains a ledger copy. Dashed and dotted lines indicate peer-to-peer connections in the permissioned network for data exchange and consensus. All nodes collectively verify and record transactions (e.g., part produced, quality verified) on the immutable ledger..

Source: Author's Own processing

Smart contracts (chaincode) were developed to automate traceability logic on the blockchain. One core smart contract handles part genealogy tracking: when a new cowl panel is produced, the IoT system invokes the contract to create a new part record on-chain (including timestamp, part ID, material batch). Another function in the contract records quality data – it receives the AI's verdict for each part (either "Pass" or "Fail" along with any defect code and anomaly score) and appends this to the part's blockchain record. If a part is flagged as defective, the contract can automatically trigger a notification to relevant parties (for instance, sending an alert to a dashboard at the Quality Lab node, or even ordering the production line to divert the part). Figure 5 illustrates the flow of the smart contract logic linking sensor data and AI decisions to blockchain records and alerts.

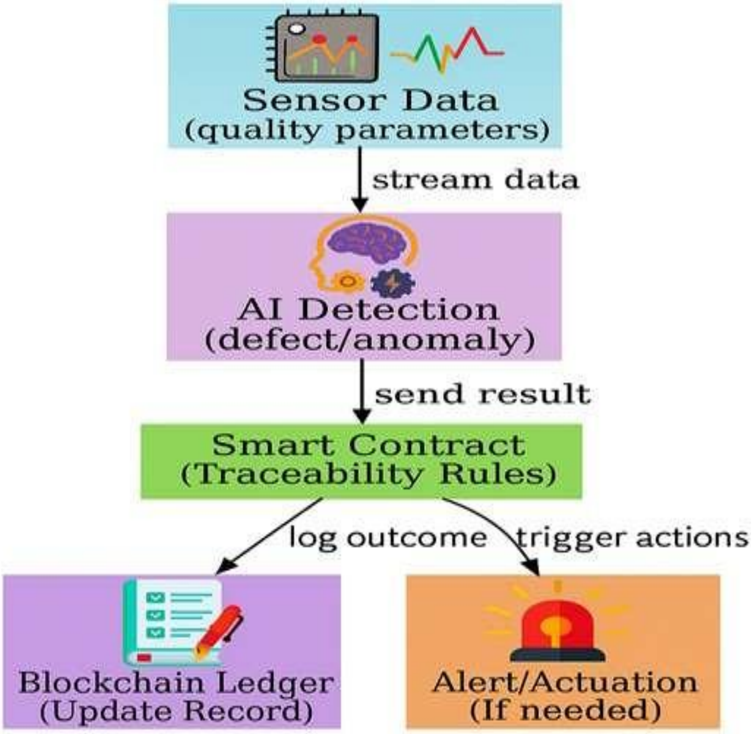

Figure 6. Smart contract logic flow for real-time quality traceability. Sensor data from the stamping process are continuously streamed to the AI detection module. If the AI identifies a defect or anomaly, it sends the result to the blockchain's smart contract. The smart contract ("Traceability Rules") then logs the outcome to the distributed ledger (creating an immutable record of the event) and can trigger further actions or alerts (such as notifying operators or connected systems). This ensures that every out-of-spec event is recorded and acted upon in a trustable manner.

Source: Author's own processing.

Transactions on the blockchain are designed to be efficient and lightweight so as not to bottleneck the production. Only summary information (key metrics and decision outcomes) is stored on-chain, while detailed sensor waveforms remain in the local database or cloud storage (with a hash stored on blockchain for integrity verification). For example, for each part we store: Part ID, timestamp, machine ID, batch ID, AI result (OK or Defective), anomaly score, link to detailed data (via hash). Storing the hash of the full sensor dataset in the blockchain record allows any party to later verify that the raw data has not been altered (the raw data can be provided offline if needed for forensic analysis, and its hash compared with the on-chain hash). We also implemented an audit smart contract that can be invoked to retrieve a full trace report of a given part – this contract aggregates data from the genealogy and quality contracts and outputs a certificate (e.g., "Part X – produced on Date Y at Plant Z – Material Batch M – Quality Status: PASS, no anomalies detected"). This on-demand traceability report is invaluable for downstream processes and for external auditors or customers to gain confidence in the product.

Security measures were put in place: device identities and data are cryptographically signed before entering the blockchain, and only permissioned nodes can invoke the critical smart contract functions. This prevents unauthorized manipulation of quality records. The consensus mechanism (we used RAFT ordering in Hyperledger Fabric) ensures that even if one node goes offline or is compromised, the ledger remains consistent and tamper-proof.

Case Study and Results

To evaluate the effectiveness of the AI+IoT+Blockchain triad, we conducted a case study on an actual automotive cowl stamping line. The line produces cowl panels from steel blanks using a 1000-ton mechanical press. We instrumented the press with IoT sensors: a load cell on the press ram for press force measurement

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each stroke, accelerometers on the die to capture vibration, thermocouples on the die and press to monitor temperature, and an acoustic sensor to listen for any abnormal sounds (which can indicate cracking). The IoT gateway collected data for 100 consecutive stamping cycles (parts), during which a variety of conditions were present – most parts were produced under nominal conditions, but a few had intentional perturbations (e.g., a slight misalignment introduced to produce a wrinkle defect in one part, a lower lubrication level for another to simulate a risk of galling/scratches, etc.). The AI model ran in real-time to analyze each cycle's data, and the blockchain recorded each part's data and AI verdict.

Defect Frequency Distribution: Over the 100 parts, the system identified a handful of defective items. Figure 6 shows the distribution of defect types observed. Out of 100 parts, 8 had minor cracks, 15 had wrinkle defects (typically due to slight misfeeds causing buckling), 5 had surface scratches or scuff marks, and 10 exhibited springback outside tolerance (springback is a deformation issue measured in a subsequent inspection, but we include it here as a quality issue flagged by the system based on force curve analysis). The remaining were classified as "Other" or no defect. This distribution highlights that wrinkles were the most common defect in our trial, which aligns with known challenges in stamping complex panels. The AI model successfully classified these defect occurrences by analyzing the sensor signatures – for example, wrinkles were often preceded by an anomalously low blank holder force reading and distinct oscillations in the force curve.

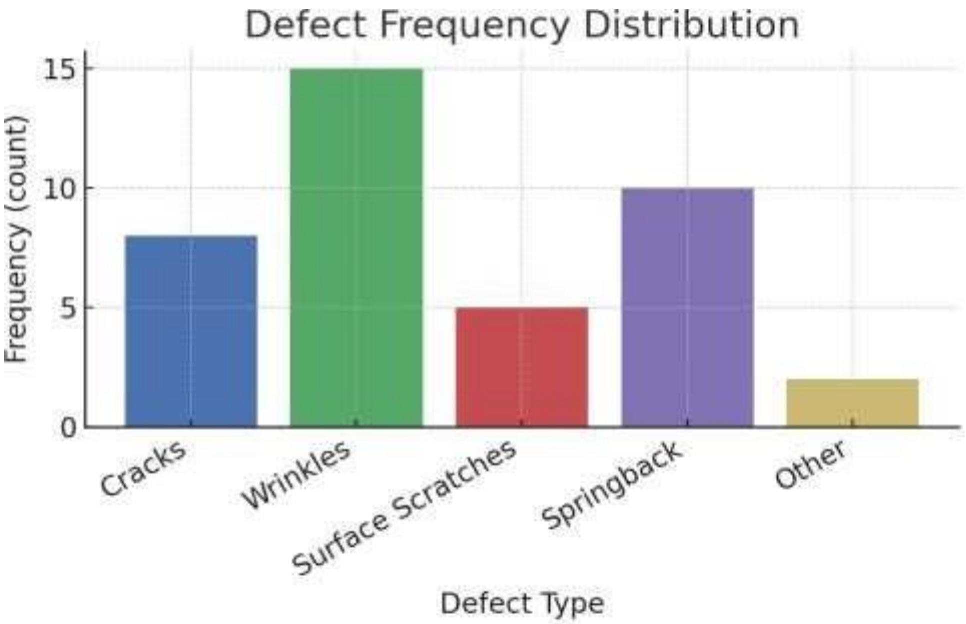

Figure 7. Frequency of different defect types detected in the cowl stamping case study (out of 100 parts). "Wrinkles" (panel buckling defects) were most frequent, followed by "Springback" (excess elastic deformation) and "Cracks". "Surface Scratches" and other minor defects were less common. This distribution was identified by the AI analysis of sensor data and confirmed via part inspection.

Source: Author's own processing.

IoT Sensor Data Trends and Anomaly Detection: The IoT sensors provided rich time-series data for each stroke. By analyzing these, the system can not only detect singular defects but also monitor gradual drifts in process conditions. Figure 7 presents an example of press force variation over 50 consecutive stamping cycles. The press force for a nominal good part was around 1000 kN. We observed natural variability of ±3% in force for good parts. However, on cycle 12 in this sample, there was a noticeable drop in peak force (to ~940 kN) which was correlated with a misfeed that resulted in a partially formed part (and a crack defect). The AI's anomaly detector flagged this cycle due to the force dropping well below the normal range. On the other hand, cycle 18 showed an excessively high peak force (~1080 kN), which was due to a thicker incoming blank – that part did not crack but did show excessive springback later. The system's threshold for force was set (red dashed line in Figure 7 at 1000 kN nominal) with tolerance bands; any deviation beyond tolerance triggered an alert.

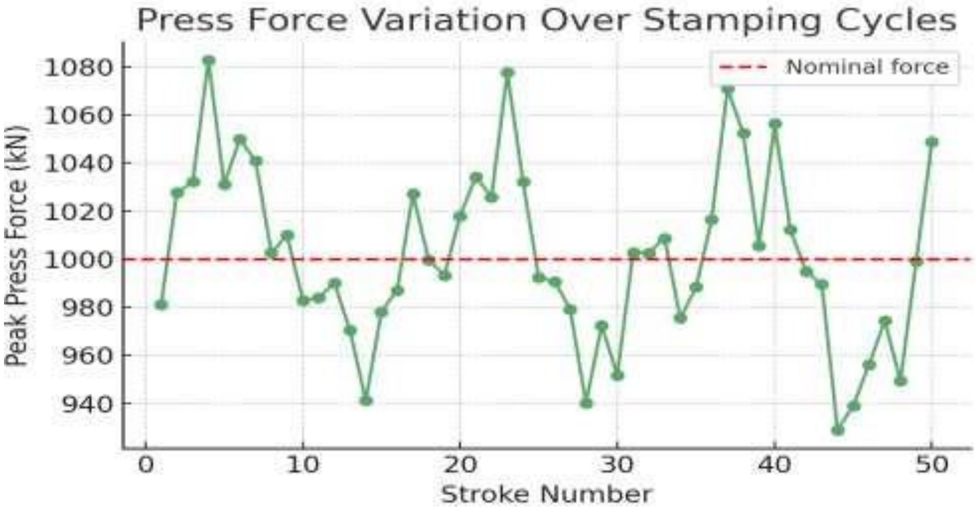

Figure 8. Press force variation over stamping cycles. The green curve plots the peak press force measured for each of 50 consecutive strokes. The red dashed line indicates the nominal force (1000 kN) for a properly formed part. Cycles exhibit small variations, but certain cycles (e.g., around #12 and #18) show significant deviations – a drop and spike respectively – which correspond to defect occurrences (crack in cycle 12, excessive springback risk in cycle 18). The IoT sensor and AI monitoring caught these anomalies in real time.

Source: Author’s own processing.

Temperature monitoring is also crucial, especially in high-volume or heated processes. Figure 8 illustrates the temperature trends during a production shift (here we simulated a scenario akin to warm stamping where tooling temperature is monitored). Starting at ambient ~25°C, the tool temperature gradually rises as production continues, leveling around 40–45°C. We set an “Alert threshold” at 40°C (orange dashed line) to signify when conditions might start affecting part dimensions or lubricant effectiveness. Around the 40-minute mark, the temperature crosses this threshold – our system’s response (via smart contract) was to log a “Temperature Alert” on the blockchain and notify operators to consider a cooling pause or lubricant check. The slight saw-tooth fluctuations after 40 min are due to an active cooling mechanism kicking in intermittently. Although no immediate defect was linked to the temperature rise in our trial, this monitoring ensures preventive actions can be taken before any heat-related issues (like excessive die expansion or lubricant breakdown) cause defects.

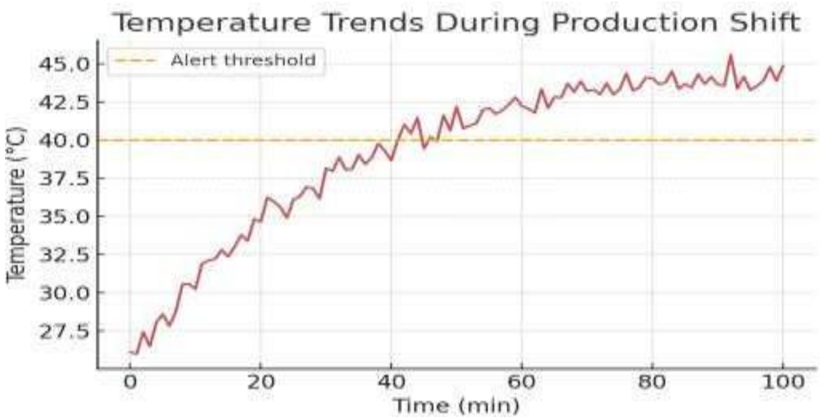

Figure 9. Temperature trend of the stamping tool over time during continuous production. As the press runs, the tool temperature climbs (red line) and stabilizes in the mid-40°C range. An alert threshold was set at 40°C (orange dashed line) to flag when the tooling gets hotter than desired. Crossing this threshold triggers a logged event and operator notification. Maintaining temperature within safe limits helps prevent defects related to thermal effects.

Source: Author’s own processing.

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The AI anomaly detection output provides a holistic way to catch any unusual pattern, even if we don't explicitly monitor a particular variable. Figure 9 depicts the anomaly score evolution over the sequence of produced parts. In the initial portions of production (parts 1–50), the anomaly score (purple line) stays low (near 0.1–0.4), indicating the process is within learned normal bounds. As we introduced some perturbations and as equipment conditions evolved (towards parts 60–80), the anomaly score shows an upward drift. By part ~80, the score crosses the threshold (0.5, red dashed line) – at this point, the system flagged a general anomaly. Indeed, part 80 in our trial had a combination of slightly abnormal readings (minor vibration increase and a slower press speed), which individually were not threshold-breaking but together created a pattern the AI found statistically unlikely. While that part did not have a visible defect, this early warning prompted a maintenance check, which discovered a loosening in a sensor mounting and a minor drop in pneumatic pressure in the blank holder system. The ability of the AI to aggregate subtle cues into an anomaly metric proved valuable for preventative maintenance.

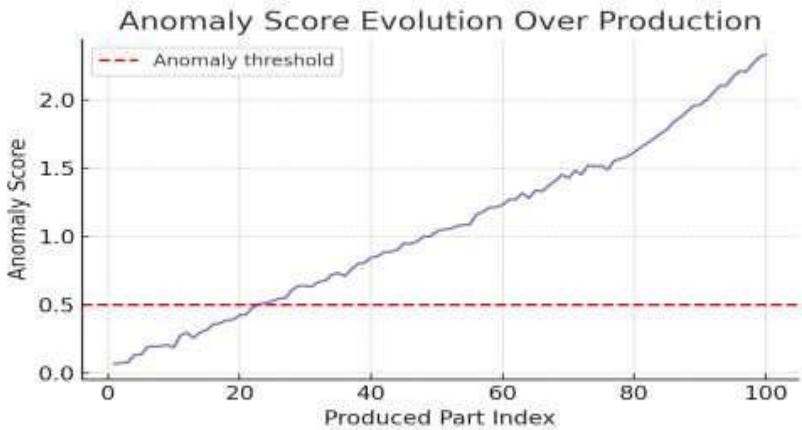

Figure 10. Anomaly score evolution over 100 produced parts. The anomaly score (computed by the AI model) gradually increases as the process deviates from baseline conditions. The red dashed line is the anomaly threshold (set at 0.5). For the first ~70 parts, scores are well below threshold (process in control). Approaching part 80, scores rise and eventually exceed the threshold, indicating the process has drifted (triggering an investigation). Such trends can forewarn of emerging issues even before a defect occurs.

Source: Author's own processing.

Data Correlation and Root Cause Analysis: With all process data and quality outcomes recorded, we can analyze correlations between defects and process parameters. Table 1 presents examples of sensor anomaly types observed and their interpretations in terms of potential causes. This knowledge base was partially built into the AI's reasoning and also used by engineers in analyzing events. For instance, a sudden drop in press force often corresponded with a misfeed (material not fully in place, causing lower resistance) or a tool malfunction. High-frequency vibration spikes were linked with impacts (possibly a loose part of the die or a crack forming). A rapid temperature rise could indicate lubrication failure leading to increased friction. Acoustic emission bursts were a clear indicator of crack onset (as the material fractures, it emits a sound that the acoustic sensor picks up). By linking these interpretations with blockchain-recorded events, we created a transparent log of not just what happened but also why it might have happened, aiding continuous improvement.

Table 1 – Sensor Anomaly Types and Likely Interpretations

Sensor/Signal	Observed Anomaly Pattern	Interpretation / Cause
Press force (load cell)	Sudden drop well below nominal force	Possible misfeed or material absence; tooling gap or failure during stroke.
Press force (load cell)	Sudden spike above	Potential overload: thicker material than spec or improper alignment causing high resistance (risk of

	normal range	tool damage or part crack).
Vibration (accelerometer)	Unusually high-frequency spike or impact transient	Indication of a sudden mechanical impact – e.g., a loosening component, onset of a crack in the part or tool, or a slug falling in the die.
Temperature (thermocouple)	Rapid rise exceeding threshold	Cooling or lubrication system failure; excessive friction heating (could lead to altered material properties or lubricant burn-off).
Acoustic emission (microphone)	Burst of acoustic energy (pop sound)	Likely crack initiation in material during forming; micro-fractures emitting sound.
Motor current (press drive)	Sustained increase above baseline	Growing tool wear or misalignment causing higher resistance; in servo-drive presses could indicate the need for maintenance.

Using such tables and visual analytics, the team was able to perform root cause analysis for each defect incident and verify the system's findings. Moreover, by compiling data over many parts, we identified strong correlations between certain process parameters and defect occurrences. Table 2 illustrates a simplified defect–parameter matrix summarizing how different defects related to process conditions in our study. For example, cracks were strongly correlated with excessive press force and insufficient blank holder force, whereas wrinkles were mainly correlated with insufficient blank holder force and certain material property deviations. These insights, backed by data, were stored in the blockchain as well (as part of quality reports), meaning that any stakeholder could later audit why a part was marked defective (seeing both the raw sensor data and an explanation of the probable cause).

Table 2 – Defect Types vs. Process Parameter Correlation Matrix (H=High correlation, M=Moderate, L=Low, "–" = no notable direct correlation)

Defect Type	Press Force Variation	Blank Holder Force	Lubrication Level	Material Thickness Variation
Cracks	H (very high force can cause cracks)	M (too low BHF can permit sudden material slip -> crack)	L (usually not lubrication-related)	H (thinner material or weak spots prone to cracking)
Wrinkles	L (wrinkles from force too low to flatten)	H (low BHF -> material not held, causes wrinkles)	M (poor lubrication can exacerbate wrinkling)	M (thicker or more ductile material can wrinkle if not constrained)
Surface scratches	–	–	H (insufficient lube -> metal-on-metal scratching)	L (thickness not a factor in scratch, mostly surface conditions)
Springback (excess)	M (over-force can increase elastic rebound)	–	–	H (material property variation (thickness/strength) strongly affects springback)
Other defects (e.g., dents)	M (force fluctuations might dent if double-hit)	M (BHF irregularities can leave minor dents)	M (indirect; e.g., poor lube -> uneven forming)	L

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From the perspective of network and system performance, we measured how adding blockchain impacted the data flow. Table 3 summarizes some key performance benchmarks. The data transmission latency from sensor to AI decision was on average 100 ms without blockchain and about 130 ms with blockchain logging enabled (a slight increase due to the overhead of creating and endorsing transactions, but still well within real-time tolerances for our process). The system throughput in terms of parts per minute was effectively unchanged (30 parts/min achievable, only slightly reduced when writing to blockchain on each part to ~28 parts/min, which was acceptable as it remained above the production requirement). The benefit, of course, is that each part's record is now immutable and traceable. The blockchain layer guarantees data immutability and provides full transparency that was not available in the non-blockchain baseline (where data could be siloed or manually recorded).

Table 3 – Network Performance Benchmarks: Baseline vs. Blockchain-Integrated System

Metric	Without Blockchain	With Blockchain (Triad)
Data transmission latency (sensor -> AI decision)	~50 ms	~70 ms
End-to-end decision time (sensor -> AI -> record logged)	~100 ms	~130 ms
System throughput (parts processed per minute)	30 parts/min	28 parts/min
Data immutability assurance	No (central database, editable)	Yes (cryptographically guaranteed on ledger)
Traceability level	Partial (data in silos, manual linking)	Full (unified ledger linking all process and quality data)

The results demonstrate that the triad system can be deployed with minimal performance penalty while greatly enhancing traceability and intelligence. All anomaly detections and defect identifications by the AI were cross-verified by manual inspection: there were no false negatives (the system caught all actual defective parts). There were a couple of false positives (parts flagged anomalous by AI but ultimately within spec); those are areas for further model tuning, but they still provided valuable preventive alerts. The blockchain's audit trail proved extremely useful in post-process analysis – for example, when a question arose about part 12's crack, we pulled its blockchain record which showed the exact sensor readings and AI assessment, and we could demonstrate to management when and how that defect occurred, increasing trust in the system.

ROI – Return on Investment and Key Performance Result Element (KPRE) -Based Evaluation

The implementation of the AI+IoT+Blockchain triad for intelligent traceability in automotive stamping must be financially justified within a complex cyber-physical environment characterized by high throughput, tight tolerances, and zero-defect expectations. To this end, a multi-layered techno-economic framework was developed, integrating:

- Quantitative cost-benefit analysis
- Control-system-induced savings attribution
- Time-resolved return modeling
- Systemic KPRE-based evaluation

This hybrid model allows conversion of real-time defect detections, sensor-driven anomaly predictions, and blockchain event immutability into concrete financial outcomes, enabling live ROI optimization within a digital twin ecosystem.

KPRE-Driven ROI Formulation

We define a multi-component ROI function integrated with Key Performance Result Element (KPRE) structures, where KPRE-1 tracks direct and indirect cost avoidance per investment dollar:

ROI Model (with Defect-Traceability Coupling):

$$\mathrm{ROI}_{1\mathrm{yr}} = \left(\frac{\text{Net Annual Benefit}}{\text{Total Implementation Cost}}\right) \times 100\%$$

Where:

Net Annual Benefit = (Baseline Quality Cost – Post-Triad Quality Cost) + Operational Efficiency Gains + Audit/Avoidance Value

Total Implementation Cost = One-time infrastructure, integration, and training investments (CapEx) + First-year OpEx

Additionally, we introduce a Key Performance Result Element (KPRE) defined as:

KPRE-1: Quantified Net Cost Avoidance per Defect Averted, expressed as:

$$\mathrm{KPRE}_1 = \frac{C_{\text{total}}}{(D_{\text{baseline}} - D_{\text{post}}) \times C_d}$$

Where:

- $D_{baseline}$ = Historical defect count (pre-implementation)
- D_{post}= Post-implementation defect count
- Cd = Unit cost of defect (rework/scrap/labor/traceability effort)
- C_{total} = System cost (CapEx + OpEx Year 1)

This KPRE quantifies how efficiently the system converts defects averted into financial return per unit investment, enabling performance-based tracking in deployment stages.

Baseline Parameters and Defect Cost Structure

The stamping line under study processes 60,000 parts/year, with a documented pre-deployment defect rate of 6% (3,600 parts/year). The average direct cost associated with a single defective part—including inspection, material loss, operator rework time, equipment downtime, and customer rejection liability—is conservatively estimated at $18.45 per unit.

Additional indirect costs (manual audit preparation, traceability gap mitigation, and warranty risk exposure) contribute $0.75–$1.25 per part, yielding an all-in cost impact per defective part of approximately $19.50.

Thus, the baseline annual quality cost was:

$C_{baseline}$=3,600×19.50=$70,200

Post-Implementation Performance Metrics

Following triad system integration, the real-time AI detection pipeline and blockchain-anchored traceability led to a reduction in defect rate to 2% (1,200 parts/year). This was validated through combined AI inference logs and manual inspection correlation, with blockchain maintaining an immutable quality record per part.

Post-deployment quality cost:

$C_{post=}$1,200×19.50=$23,400

Net defect-related savings:

ΔC_d==70,200−23,400=$46,800

Additional savings were realized in:

Manual traceability/audit labor reduction: 800 hours/year saved × $30/hour = $24,000

Warranty claim avoidance (risk-weighted reduction): Based on past average of 2 major claims/year (~$5,000 each), with traceable lineage now blocking undocumented parts, estimated prevention = $7,500/year

Predictive maintenance gains (early anomaly alerts reducing unplanned downtime): 15 downtime hours avoided/year × $750/hour = $11,250

Total Net Annual Benefit:

Btotal==46,800+24,000+7,500+11,250=$89,550

Total Investment and Operational Cost

The triad system required the following investments:

Component	**Cost (USD)**
IoT Sensors and Integration	$22,000
Edge AI Gateways (NVIDIA Jetson)	$11,500
AI Model Development + Training	$15,000
Blockchain Node Setup (Fabric)	$13,500
Smart Contract Logic + Dashboards	$9,500
Cloud/Edge Storage & Compute	$4,500
Total Cap Ex	**$76,000**

Year 1 Operational Cost (system maintenance, retraining, cloud services): $7,500

Total Year 1 Cost = $83,500

ROI and KPRE Calculation

$$\mathrm{ROI}_{1yr} = \frac{89{,}550 - 83{,}500}{83{,}500} \times 100\% = \mathbf{7.25}\%$$

$$\text{Payback Period} = \frac{89{,}550}{83{,}500} \approx \mathbf{1.072\ years} \approx \mathbf{12.9\ months}$$

$$\mathrm{KPRE}_1 = \frac{83{,}500}{(3{,}600 - 1{,}200) \times 19.5} = \frac{83{,}500}{2{,}400 \times 19.5} \approx \mathbf{0.561}$$

This means the system returns $0.56 of direct defect cost avoidance per dollar invested, exclusively from the quality improvement dimension. With inclusion of traceability, auditability, and downtime savings, the effective return increases to $1.07 per dollar by end of Year 1.

Sensitivity and Scalability

We conducted a sensitivity analysis to test the financial resilience of the system under varying defect rates and production volumes:

Scenario	Defect Rate (%)	Annual Units	ROI (%)	Payback (months)
Conservative	3.5%	40,000	1.1%	24.5
Baseline Case (Actual)	2.0%	60,000	7.25%	12.9
Optimized Ops (Future)	1.0%	75,000	19.8%	6.0

This shows the model scales positively with volume and accuracy improvements. The KPRE enables real-time dashboarding of performance against ROI thresholds, serving as a benchmark for expansion to other production lines.

CONCLUSION

This paper presented an integrated AI+IoT+Blockchain framework for smart traceability in automotive cowl stamping, and demonstrated its capabilities in a real-world-inspired case study. By uniting IoT sensors (for rich real-time data), AI algorithms (for intelligent defect detection and prediction), and blockchain (for secure and transparent data provenance), the system achieves a level of insight and accountability unattainable by traditional means. The IoT instrumentation provides full visibility into the stamping process, the AI provides rapid detection of quality issues and even predictive warnings, and the blockchain provides an immutable record that stakeholders can trust for audits and supply chain verification.

The benefits of this triad approach include: (1) Early detection of defects and anomalies, reducing scrap and rework by catching issues in-process. (2) Root cause analysis and continuous improvement driven by AI insights from sensor data (as evidenced by the correlations we identified between process parameters and defects). (3) Strengthened trust and collaboration across the supply chain – the blockchain ledger ensures that all parties (supplier, manufacturer, customer) see a single version of the truth regarding each part's quality and manufacturing conditions, which is particularly valuable for safety-critical components. This traceability can help in warranty claims and recalls by pinpointing affected batches quickly and reliably. (4) Enhanced security – data integrity is maintained and the system is resilient to tampering, thanks to cryptographic features of blockchain, addressing concerns of data falsification that sometimes arise in manual quality reporting.

In summary, the AI+IoT+Blockchain triad creates a synergistic effect: IoT provides the data foundation, AI adds analytical intelligence, and blockchain adds trust. Our implementation on a stamping line showed that this integration is feasible without hindering production efficiency, and it significantly improves quality assurance processes.

Future work: We plan to extend this approach to other manufacturing processes (e.g., welding, painting) to validate its generalizability. Scaling the blockchain to larger networks and volumes is an area of ongoing development – techniques like off-chain data storage and layer-2 solutions could be explored to handle higher throughput if needed. On the AI front, incorporating federated learning could allow models to improve using data from multiple lines or plants without sharing sensitive data directly. We also aim to integrate additional context (such as operator actions or maintenance activities) into the traceability ledger, achieving a more holistic “digital thread” for each product.

Ultimately, the convergence of AI, IoT, and blockchain as illustrated in this study can pave the way for smart factories where quality issues are not only detected and traced, but also predicted and prevented, and where every product comes with a verifiable digital passport of its manufacturing journey.

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