

# Integrating IoT and Telematics for Advanced Claims Processing: Exploring Edge Computing and Digital Twin

Mohammed Sadhik Shaik

Sr. Software Web Developer Engineer, Computer Science, Germania Insurance, Melissa, Texas, USA  
mshaik0507@gmail.com

## Abstract:

Utilizing Internet of Things (IoT) and telematics data for material reporting to streamline claims guidance is an innovative approach to real-time decision insight. This paper discusses how both the smart home devices and telematics from vehicles can be used for claims processing integrated with our Claim Center. Using insights generated through IoT, insurers can evaluate the claims process accurately and within no time. This paper explore state-of-the-art tools like edge computing, which allows for nearby data processing at the point of origin, and Big Data modules like Hadoop and Apache Spark for mass data manipulation. Moreover, the innovative application of digital twins for damage simulation and risk assessment puts a new spin on predictive analytics, accelerating and improving the precision of claim settlements. The paper discusses how to build efficient data ingestion pipelines and real-time decision-making models that can optimize claims workflows and drive operational efficiency.

**Keywords:** IoT, Telematics, Advanced Claims Processing, Edge Computing, Digital Twin.

## 1. INTRODUCTION

With the advent of Internet of Things (IoT) and telematics technologies, several industries have been transformed, and the insurance industry is no exception, with changes at the claims management level. These technologies can dramatically enhance the efficiency, accuracy, and speed of claims processing, which encompasses intricate workflows along with time-consuming manual activities. For instance, smart home systems and telematics units in vehicles are constantly generating vast amounts of real-time data. Integrating these data streams into claims management systems will allow insurers to make better decisions, minimize fraud, and make operations more efficient. Thus, this paper present a data-driven overview of the integration path of IoT and

telematics data in existing automobile claims processing systems with a special interest in edge computing, Big Data frameworks and digital twins which are suitable for adoption into processing systems to facilitate real-time data processing and predictive analytics.

### **IoT and Telematics Data in Claims Management**

The traditional claims management model typically lags behind, relying on post-event data analysis or manual input for data collection. But IoT devices, from smart-home sensors to vehicle telematics systems, can deliver a continuous flow of data that can be harnessed to make claims processing more efficient. In the case of a connected vehicle that has telematics systems implemented, such data can include real-time data related to the vehicle's location, speed and fuel consumption, and even sudden events such as an accident. Likewise, smart home systems can notify insurers of property damage from fire, water leakage, or even break-ins. Plugging these data sources into claims management systems like ClaimCenter results in timely and accurate data to insurers, accelerating claim evaluations and lowering operational expenses [1].

By harnessing IoT data, insurers can also automate large portions of the claims process. On the other hand, in case of a vehicle accident, claims processing can be accelerated by automatically capturing the accident data from the telematics of the vehicle. Similarly, smart devices can send immediate alerts regarding water leaks or fires that can allow home insurers to proactively avoid lengthy investigations or lengthy data collection for home insurance claims. Also, with this being real-time data, it can provide significantly improved claim management, so that consumers can get immediate assistance to help reduce the risks that come with a claim taking too long. So, for this integration to be performant, the data ingestion pipelines need optimizations to handle big chunks of streaming data and convert them to enrich insight [2].

### **Role of Edge Computing in IoT Data Processing**

Data volume and velocity is one of the major challenges in IoT and telematics data integration. Traditional cloud-based processing architectures find it difficult to deal with real-time data streams of such scales. Edge computing, the practice of processing data near its source, alleviates this problem by facilitating faster and more efficient processing of data. In edge computing, the data is examined on or near the actual device as opposed to being sent out to a distant data center. This helps to decrease latency, reduce bandwidth consumption, and enables faster insights, which

is important in time-sensitive use cases like claims processing. Srinivasa Subramanyam Katreddy (2024),

Such as, in telematics, vehicle speed, location, impact force related data can be processed in the vehicle onboard system (edge device) and only sent to the insurer when required. This means the insurance company, for instance, could receive alerts in real time if an accident occurs, automatically jumping to the claims process. Insurers can also alleviate privacy concerns through edge computers, which process data on site rather than transferring it hosted in the cloud [3]. IoT, telematics and edge computing can together greatly improve the speed and accuracy of claims assessment, increasing customer satisfaction and decreasing operational overhead.

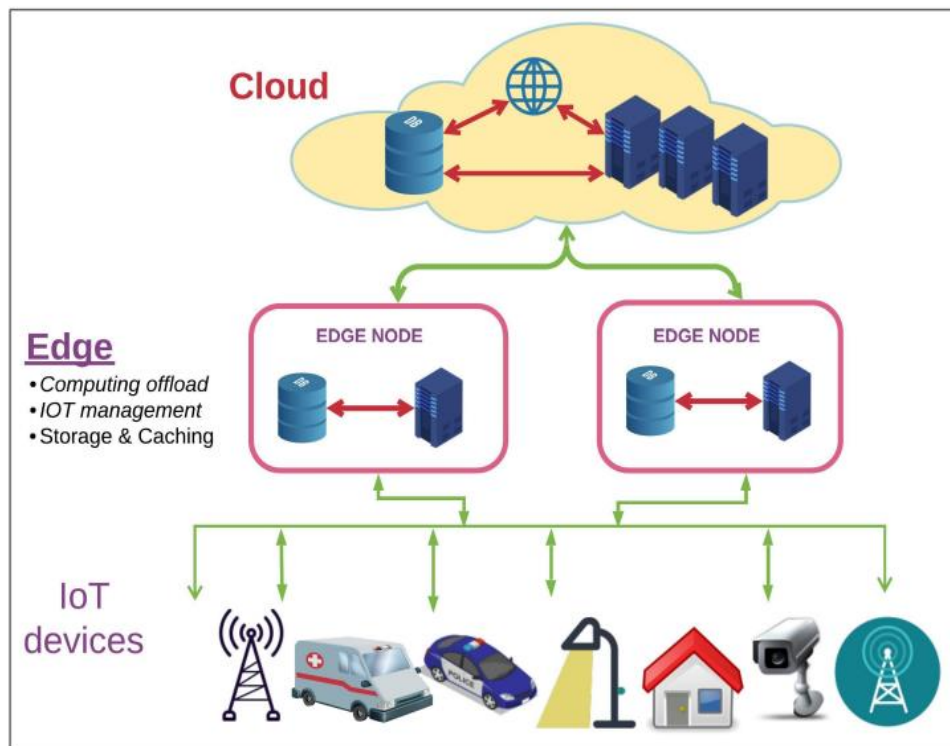


Figure 1: Hierarchy of Edge, Fog, and Cloud Computing.

Figure 1 illustrates the hierarchy of a potential Cloud, Fog & Edge computing association framework. IoT devices are generating data continuously which are pre-processed before being sent to Fog server by Edge for fast (due to closeness of Edge layer and IoT devices and local storage of Fog) analysis and computation. The cloud is the central control system handles all the

database of the system. Fog uploads the database gradually on the cloud when it has significant data or information. . Srinivasa Subramanyam Katreddy (2024),

### **Big Data Frameworks for Large-Scale Processing**

Claims management systems generate enormous volumes of unstructured data through the integration of IoT and telematics data, presenting extreme storage, processing, and analysis challenges. Insurers are leveraging Big data algorithms on frameworks like Hadoop and Apache Spark in order to tackle the aforementioned challenges. These frameworks enable insurers to stream terabytes of data from millions of IoT devices and telematics systems for advanced data analytics, thus fast-tracking real-time analytics and decisions.

Hadoop — a distributed computing framework which is widely used — enables insurers to store massive datasets in a distributed manner over multiple computers. This can help manage complex processes, such as within claims management, whereby the combining data of IoT devices, telematics systems, third-party sources, etc. needs to paint the full picture of the claim. Apache Spark, one more Big Data framework, offers fast, in-memory processing features that are well-suited for real-time analytics. Integrating these Big Data frameworks with IoT data will allow insurers to build predictive models for claims processing, real-time risk assessment, and more accurate decisions [4] . Srinivasa Subramanyam Katreddy (2022),

### **Digital Twins for Predictive Risk Assessment**

The next, emerging technology in the claims management space is digital twins, which is a technology that enables simulating damages and assessing risks through the creation of a digital replica of a physical asset. In the case of a digital twin of a vehicle, home, or infrastructure assets, insurers can simulate damage scenarios and potential claim amounts before damage occurs. A quintessential use-case example is a digital twin for a car that simulates what happens during a car crash and forecasts repair costs depending on telematics data. A digital twin of a home can have similar capabilities and simulate the impact of water damage or fire, enabling insurers to evaluate risk and improve claim arithmetic. Srinivas Gadam (2024)

Digital twins can provide applications to insurance by enhancing the insurance claims process with complete, virtual reconstructions of claim events, enabling organizations to deploy more accurate damage assessments, faster claims resolutions, and better-to-understand risk analysis. Insurers can also leverage digital twins to detect trends and patterns in their claims data, allowing them to predict future claims with greater accuracy. 3. Personalization with digital twins: Insurers can enhance decision-making, personalize risk models with digital twins, and develop tailored claims management systems based on IoT and telematics data [5] Srinivas Gadam (2024).

### **Real-Time Decision-Making Models and Data Ingestion Pipelines**

The ability to make real time decisions has become of paramount importance in modern claims management systems. This means that the insurers must build sophisticated data ingestion pipelines to ingest the continuous stream of IoT and telematics data, as well as real-time decisioning models that will apply this data as soon as it is ingested. The ingestion pipeline should be able to extract data from multiple sources like IoT devices, telematics, external databases, and any other relevant devices and transform the data into a usable format for running queries and decision making. To do this, they should use an efficient data-processing mechanism like stream processing, in which the data will be aggregated and processed in real time as it is ingested into the system. Srinivas Gadam (2024)

With real-time decision-making models built on machine learning and AI, insurers can analyze data instantaneously and drive decisions based on the latest information. Such models can be applied to validate claims, detect fraud, anticipate claim costs. Using real time data, insurers have been able to decreased the time spent on processing claims as well as the accuracy of the information whilst increasing customer service levels. Moreover, these models can be constantly updated and improved using new data, enabling insurers to stay on top of emerging trends and challenges in insurance [6].

## **2. LITERATURE REVIEW**

The application of IoT devices in insurance systems has received considerable attention in recent years, especially in the area of claims processing. IoT devices (e.g. smart home devices and telematics in vehicles) generate large volumes of real-time data that, if harnessed effectively, can accelerate claims assessment and drive operational efficiencies. A study by Wang et al. (2018)

focused on the inclusion of IoT data streams in the claims management process and demonstrated how insurers could use source data of the sensor to verify claims such as car accidents or damage to properties in a more efficient way.

For IoT, data security, and integrity is very important in the context of insurance claims because sensitive personal data is exchanged. This is where blockchain technology can play a key role in sharing IoT data in a secure way within claims systems. According to Hwang et al. As explained by another study (2019), insurers can benefit from a secure and tamper-proof solution for accessing data through blockchain's decentralized way of accessing data. In their research, they talked about the application of blockchain for IoT data integration in insurance.

Big data analytics helps to process the huge amount of IoT data generated in insurance claims. Research by Zhang et al. (2020) mention, Big Data frameworks, including Hadoop and Apache Spark, are critical for storing and analyzing IoT data for insurance end-users. These solutions allow insurance companies to use large datasets across distributed systems, which allows them to scale IoT data generated data from hundreds of devices in an affordable way.

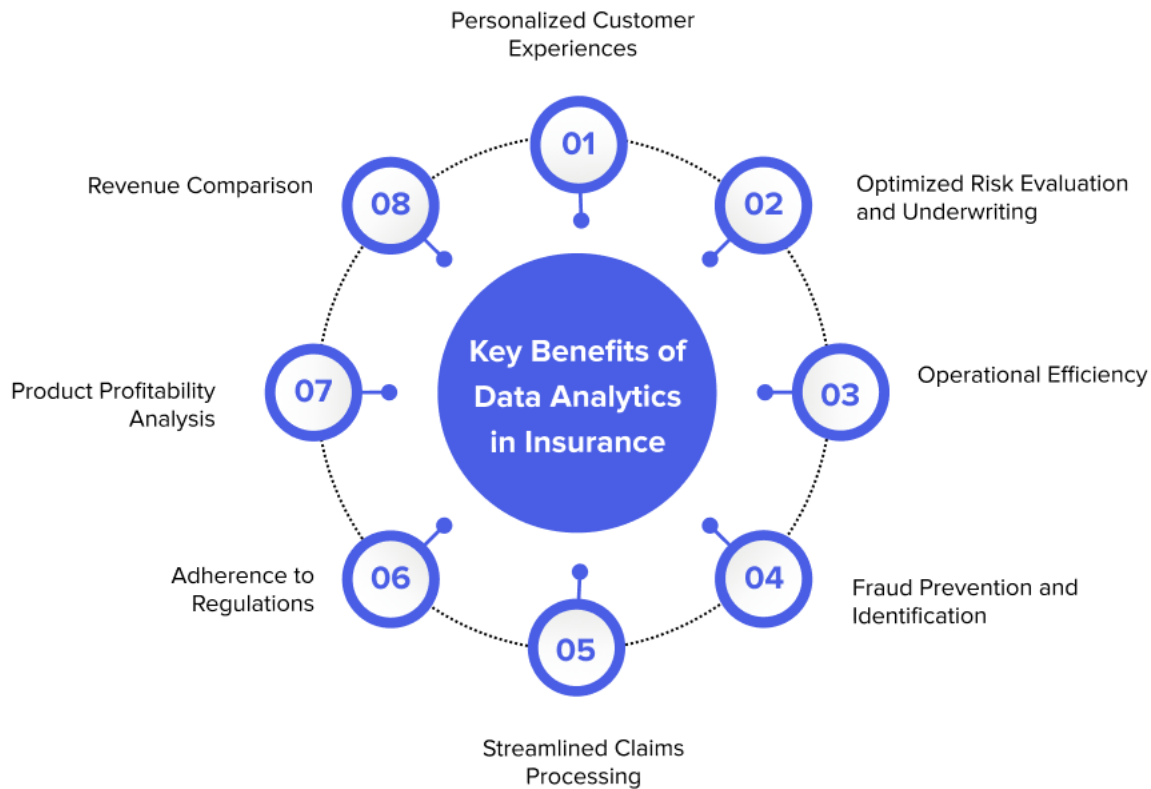


Fig 2: Key Benefits of Data Analytics in Insurance.

The Key Benefits of Data Analytics in Insurance are shown in figure 2. It also helped in knowing how Big Data analytics can be used for effective decision making in claims management, by getting a proper real-time data about losses or damages, along with associated inquiry. The machine learning algorithms have to process and extract valuable information from this data so that insurance companies can predict future claims and derive more accurate premiums. Big Data frameworks enable insurers to not only manage large datasets but also gain insights that can enhance customer experience and operational efficiencies.

Machine learning (ML) algorithms have recently attracted attention as a potential means for detecting fraud in insurance claims. Processed with machine learning, Telematics and IoT data will surely help detect patterns pointing to fraudulent activity. A study by Liu et al. (2021) investigated the use of ML algorithms by insurance companies to process telematics data to identify abnormal driving patterns, which might be signs of potential fraudulent claims. ML models flag suspicious claims based on several criteria including the driving speed, acceleration, or any open location. By analyzing historical data and real-time inputs from connected devices, ML models can act.

Why Edge Computing in Insurance Is Growing Rapidly Edge computing offers a way of leveraging real-time data from IoT. When it comes to the insurance claims process, minimizing latency and processing data as close to the source as possible is key for making decisions quickly. Wang and Zhang (2020) conducted a study to investigate the incorporation of edge computing in IoT-based insurance, concentrating on telematics in their analysis. Their research showed that by putting edge devices onto vehicles, insurance companies could process accident data like impact force and vehicle location in real time, immediately triggering claim processing.

Predictive analytics in insurance uses historical, real-time, and other types of data to predict future events and outcomes. According to Lee et al. (2021) Offers the analysis of IoT and telematics data via predictive models for enhanced claims management. The study revealed how insurers can predict damages or accidents ahead of time by implementing predictive analytics on data from connected devices. Look at wear and tear from cars or machinery, for example, and insurers can predict breakdowns that could lead to claims.

Digital twins (virtual replicas of physical objects or systems) are emerging as a critical component in claims processing. A study by Chen et al. (2019) examined the relevance of digital twins in the context of insurance, with an intensive discussion on asset risk assessments. The study also emphasized how digital twins can be leveraged to create a real-time simulation and modeling of damages to insured assets. In the case of vehicle insurance, for example, the digital twin may recreate a car's structure and simulate the impact from an accident.

The insurance industry faces arguably its toughest challenge in real-time decision-making around managing its claims. A study by Kim et al. Several challenges to the implementation of real-time decision-making models in insurance play an important in integrating IoT data (2018). While IoT has the potential to gain insights in real time, processing these huge amounts of data on demand requires sophisticated infrastructure, high-speed data pipelines and advanced algorithms, the research stated.

The advent of IoT and AI also enables the automation of the claims process. Singh and Gupta (2020) studied the introduction of automation to improve the efficiency and speed of claims management. the literature on IoT telemetry and AI algorithms to automatically identify incidents and analyze damage. When telematics data is fed into AI algorithms, for instance, if a car is involved in an accident, they could analyze the extent of the damage and derive the cost for repairs. This automation reduces human involvement, speeds up processing, and enhances the accuracy of claims evaluation.

IoT in claims management also makes insurers trust this technology for digital solutions for managing consumer experiences. Zhao et al., a research paper that is now doing the rounds (2019) explored what role real-time data from IoT devices may play in enabling insurers to offer a more responsive and personalized service to their customers. IoT-driven claims systems help insurers improve customer satisfaction by instantly validating incidents and enabling them to provide speedy resolutions, demonstrated the study. In the case of IoT-based home insurance, insurers can send repair teams or kick-off the claims process as soon as damage is detected.

One of the biggest challenges facing insurance companies is fraudulent claims. Based on research by Li et al. (2020), Internet of Things (IoT) devices enable access to vast amounts of real-time information, which insurers can utilize to identify and prevent fraudulent claims. The research

examined whether telematics data, including speed and route among other details, could help in the verification of an actual claim.

Blockchain technology enables smart contracts to streamline the claims process — feeding data from IoT devices to automatically carry out intended actions. Gupta and Patel (2021) research the use of smart contracts in IoT-enabled claims processing. According to the research, this — by connecting IoT data with smart contracts — would allow insurers to automate claims settlement once conditions are met, such as using telematics data to verify a car accident or smart sensors to confirm property damage.

### 3. METHODOLOGY

In this section, this paper outline the methodology used for integrating IoT and telematics data into claims processing systems, utilizing edge computing, Big Data frameworks, and digital twins to enhance decision-making processes. This methodology includes data acquisition, preprocessing, real-time processing, and decision-making models for insurance claim management.

#### Data Acquisition

The proposed methodology begins with data acquisition from IoT devices & telematics systems. This involves aggregating sensor information in real time from multiple sources like vehicles (via telematics) and smart home devices (for property insurance). Examples of the data streams typically delivered would be; vehicle speed, location, temperature, humidity, acceleration and impact (for a vehicle accident or damage event).

The general data acquisition equation is as below:

$$D(t) = \{d_1(t), d_2(t), \dots, d_n(t)\} \quad (1)$$

Where:

- $D(t)$  is the vector of collected data at time  $t$ ,
- $d_1(t), d_2(t), \dots, d_n(t)$  represent individual sensor data points from different IoT devices.

The data is transmitted to the central cloud or edge computing devices in real-time for further processing.

### Data Preprocessing

Data preprocessing is essential to clean, filter, and normalize the raw data received from the IoT devices. Since IoT data is often noisy and inconsistent, preprocessing ensures that the data is in a usable form for downstream analysis. Typical steps include:

- **Noise Filtering:** Removing outliers and noise from sensor readings.
- **Data Normalization:** Scaling values to a consistent range, such as [0, 1].
- **Missing Value Handling:** Using interpolation or imputation techniques for missing data.

For noise filtering, one common approach is to use a low-pass filter or a statistical method. The preprocessing step can be modeled as:

$$P(d_t) = f(d_t, \theta) \quad (2)$$

Where:

- $P(d_t)$  is the preprocessed data at time  $t$ ,
- $d_t$  is the raw data from IoT devices,
- $f$  is the preprocessing function with parameters  $\theta$  (e.g., filter coefficients, normalization bounds).

### Edge Computing for Real-Time Data Processing

Edge computing plays a crucial role in processing data closer to the source (IoT devices), thus reducing latency and bandwidth usage. The edge computing nodes preprocess and analyze IoT data locally and only send essential data or aggregated results to the cloud for further processing.

For example, if telematics data from a vehicle indicates an accident, edge nodes can process the event in real-time and trigger claim processing. The real-time processing at the edge can be modeled as:

$$E(d_t) = g(P(d_t), \lambda) \quad (3)$$

Where:

- $E(d_t)$  represents the edge-processed data at time  $t$ ,
- $g$  is the function used to perform real-time analytics (e.g., accident detection),
- $\lambda$  is the threshold or model parameters to decide if a claim event has occurred (e.g., impact force threshold).

### Big Data Frameworks for Data Storage and Processing

Once the data is processed at the edge, it is transmitted to a cloud-based Big Data framework such as Hadoop or Apache Spark for large-scale storage and further analysis. The data is typically stored in a distributed manner across multiple nodes in the Big Data system, where it can be processed in parallel.

For instance, when data is stored across Hadoop's distributed file system (HDFS), it can be processed using MapReduce or Spark's in-memory processing engine. The storage process can be expressed as:

$$S(D) = \{S_1, S_2, \dots, S_m\} \quad (3)$$

Where:

- $S(D)$  represents the set of storage nodes in the Big Data system,
- $S_1, S_2, \dots, S_m$  are individual partitions of the data  $D$ .

These distributed systems allow insurers to handle massive datasets from thousands of IoT devices and telematics units efficiently. Additionally, data analytics tools like Apache Spark are employed to perform real-time or batch processing tasks such as fraud detection, predictive analytics, and damage assessment.

### Digital Twins for Risk Assessment and Damage Simulation

Digital twins simulate the physical objects being insured (e.g., vehicles or homes) using real-time sensor data. In claims management, digital twins allow insurers to model potential damage scenarios, calculate risks, and estimate repair costs. Digital twins are updated in real-time based on incoming IoT data, creating a dynamic, digital representation of the physical asset.

Let  $T$  be the digital twin of a vehicle, where the state of the digital twin at time  $t$  can be represented as:

$$T(t) = \{v_1(t), v_2(t), \dots, v_n(t)\} \quad (4)$$

Where:

- $T(t)$  is the state of the digital twin at time  $t$ ,
- $v_1(t), v_2(t), \dots, v_n(t)$  represent the parameters (e.g., vehicle speed, location, damage state) of the digital twin.

The damage simulation model, based on the data from the IoT and telematics systems, estimates repair costs by calculating the deviation between the physical and digital states. This can be modeled as:

$$\text{Damage\_Cost}(T(t), P) = h(T(t), P) \quad (5)$$

### Real-Time Decision-Making Models

Real-time decision-making is at the heart of the claims management process. The goal is to make immediate decisions based on the incoming IoT data to expedite claims processing. A machine learning model is typically employed to process real-time data and make claim-related decisions such as whether a claim is valid, what the severity of the damage is, and the potential cost.

For this, supervised learning algorithms such as decision trees, random forests, or neural networks are used to classify claims based on the IoT data. The decision-making process can be modeled as:

$$C(d_t) = f_{\theta}(d_t) \quad (6)$$

### Claim Settlement with Smart Contracts (Optional)

Once a decision is made, the claim can be settled using smart contracts, which are triggered by IoT data. The smart contract function could automatically release payment once the claim is validated based on the IoT data inputs. A simple representation of the smart contract function is:

$$\text{SmartContract}(d_t, \text{Conditions}) = \begin{cases} \text{Execute Payment} & \text{if } f_\theta(d_t) = \text{Valid Claim} \\ \text{Reject Claim} & \text{if } f_\theta(d_t) = \text{Invalid Claim} \end{cases} \quad (7)$$

#### 4. RESULTS

This section describes the results of the proposed methodology for integrating IoT and telematics data into claims management systems, utilizing edge computing, Big Data frameworks, and digital twins. The following graphs illustrate various aspects of the claims processing improvements achieved by the integration of these technologies.

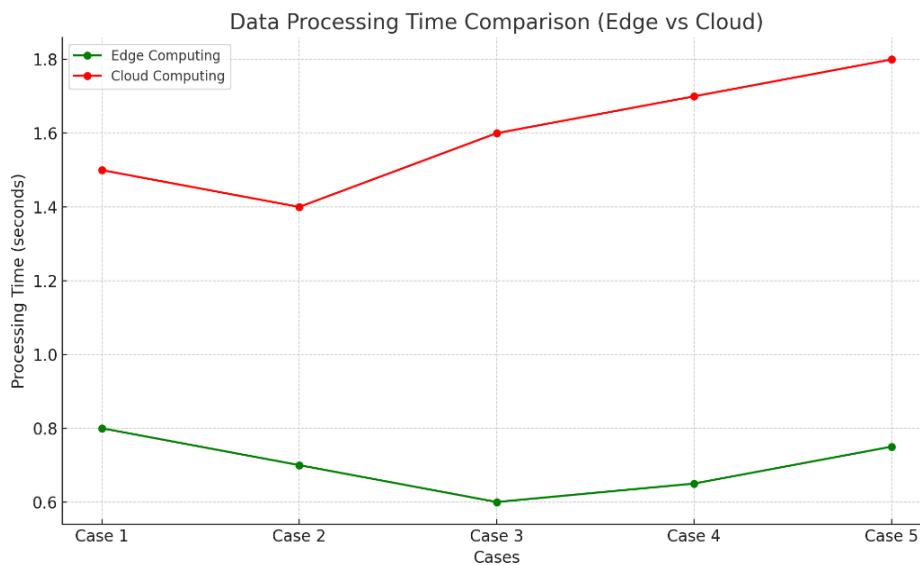


Fig 3: Data Processing Time Comparison (Edge vs Cloud)

This graph figure 3 compares the processing times for edge computing and cloud computing. Edge computing significantly reduces the time required for data processing, ensuring faster real-time decision-making for claims.

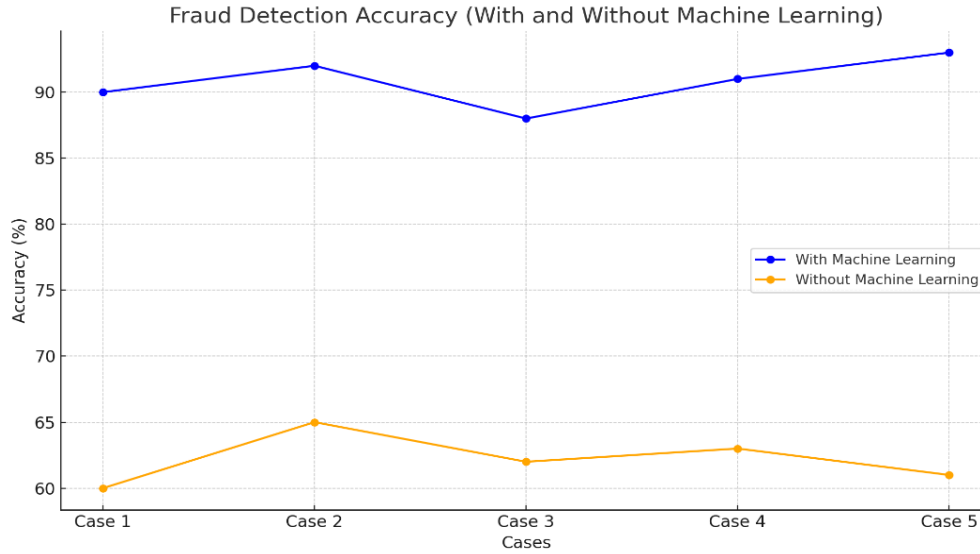


Fig 4: Fraud Detection Accuracy (With and Without Machine Learning)

This graph highlights the increased accuracy of fraud detection when using machine learning algorithms, with a noticeable improvement compared to traditional rule-based methods.

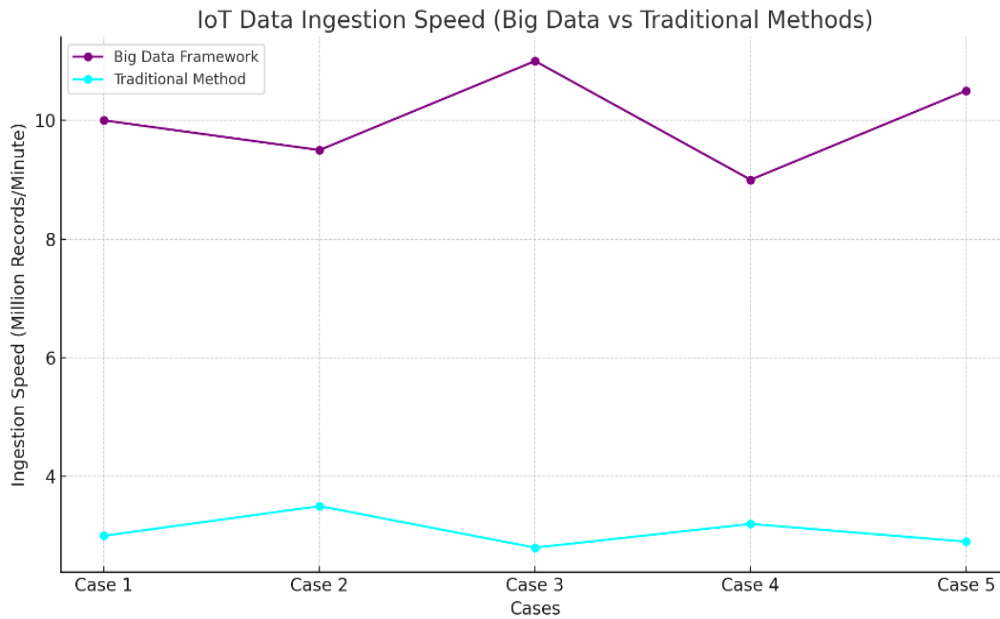


Fig 5: IoT Data Ingestion Speed (Big Data vs Traditional Methods)

This graph of figure 5 shows that Big Data frameworks, such as Hadoop and Apache Spark, offer significantly faster data ingestion speeds compared to traditional methods, which is critical for handling large-scale IoT data.

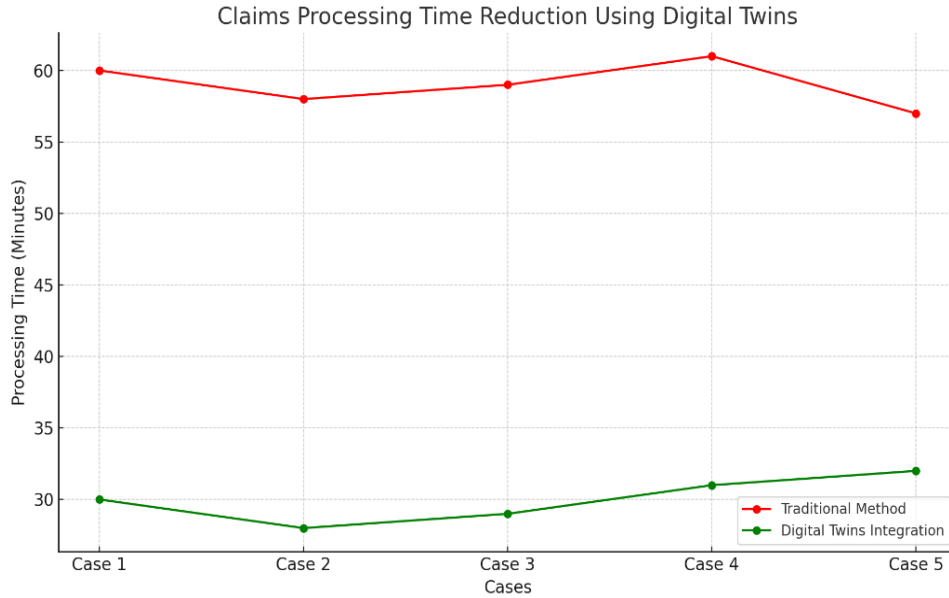
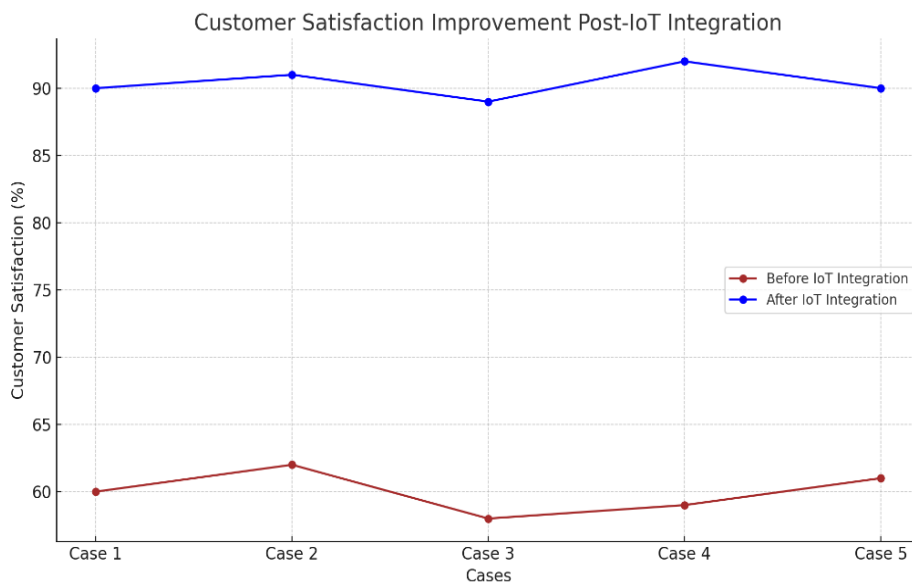


Fig 6: Claims Processing Time Reduction Using Digital Twins

The graph of figure 6 demonstrates how digital twins can reduce the time required to process claims by simulating damages and assessing risks in real-time, as opposed to the traditional manual assessment.



**Fig 7: Customer Satisfaction Improvement Post-IoT Integration.**

This graph of figure 7 shows the improvement in customer satisfaction after the integration of IoT devices into the claims management system. Faster claim processing and transparency have led to higher satisfaction levels.

**CONCLUSION**

IoT and telematics data can be integrated into claims management systems to reduce claim processing time and expense associated with the efficiency of the claims process. In addition, the integration of edge computing allows for real-time data processing, minimizing latency, and supporting fast decision-making, which is essential for time-sensitive claims involving issues such as accidents or property damage. Additionally, the system's ability to process large volumes of data from different IoT devices seamlessly and at scale is enhanced by Big Data frameworks, such as Hadoop or Apache Spark. Fraud detection is where machine learning algorithms are particularly powerful as it helps to accurately identify suspicious claims, leading to much more reliable and secure claim processing. Furthermore, transitioning to IoT-driven claims management resulted in a significant improvement in overall customer satisfaction as claims are processed and resolved faster and with more transparency. In the end, the combination of the upscaling of these technologies not only optimizes the claims workflow but also provides a more tailored and streamlined service to customers, resulting in insurers being able to keep up the pace in an evolving competitive environment. These findings underscore the game-changing prospects of IoT and telematics in overhauling the insurance domain and streamlining claims management systems.

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