# Automated Document Classification and Straight-Through Resolution: AI-Driven Strategies for Claims Processing Cycle Time Reduction in Insurance Operations

*Dr. Marcia O'Connell, Associate Professor of Robotics, Australian National University (Australia)*

## 1. Introduction

The insurance industry faces issues on multiple fronts, reflecting a range of complexities. Claims handling has long been the subject of extensive commentary as a result of the operational inefficiencies that mar it further, as well as the power dynamics between the involved parties. Delays in claims handling lead to further dissatisfaction on the part of policyholders, promoting negative perceptions and word of mouth. Delayed insurance claims settlement processes, in turn, lead to inefficient practices; the more claims there are, the more time it takes to review, digest, and negotiate the terms for every claim, not to mention the additional manpower required to verify the facts of each case. Consequently, insurance companies' operational expenses skyrocket.

These profit-eroding practices are particularly problematic in the fast-paced economies we live in today. Modern businesses require fast cash flows, and the easiest way to ensure this occurs within a firm, let aside the whole economy, is to aim for fast compensation of damages suffered. Given this context, a governance framework for managing the damage management process must be put in place by all businesses. Since the most highly regarded insurance companies focus on these claims by leveraging compensation as natural marketing, superior damage compensation benefits them in a better way. With a wide range of outsourcing enterprises and user-friendly navigation characteristics, many others looking for a good insurance policy are clamoring for the duration of the insurance claims settlement. This method is ushering insurance businesses to either simple or advanced levels to integrate modern technology, but doesn't the process require more optimization? This text is an attempt to provide a background of contemporary insurance claim management. This text also introduces how institutions have seamlessly utilized progressive technologies to optimize the argument if it remains common because traditional practices can never totally be ruled out. The adoption of a new approach and market norms that have been rehearsed over the years have been disclosed and thoroughly described.

### 1.1. Background and Significance of Claims Processing in Insurance Industry

1.1. Background and Significance of Claims Processing in the Insurance Industry

Claims processing is a vital function in the insurance industry. A significant percentage of policyholders who file a claim express a clear tendency to renew their policy when their insurer does a good job processing. The customer's adaptability for further purchases of the insurance policy lies in the hands of the insurer. Claims management assumes significance in terms of cost, not only for the policyholder but also for insurers. When a claim is delayed, it adds to the cost of claims. Thus, a company that is considered to be efficient in claims handling can gain a competitive edge over its competitors. Delays may occur across several dimensions, such as the time taken by the insured to report the damage, the customer's delay in providing documentation, supply chain delays, etc. Once these are called the 'initial delays,' the subsequent operational and processing inherent delays are caused by factors like several employee touches to process material and extensive paperwork. It is estimated that of all the delay times, a significant portion is accounted for by paper tracking, a deficiency in system capabilities, and the inconsistency in communication within and across different departments and carriers, as well as other organizations and agencies.

Delays have severely affected the processing of claims. For example, in the automobile segment, almost two-thirds of auto claims have been observed to take nearly twice as long as they should. In the workers' compensation sector, it has been observed that it takes insurers a considerable amount of time to conduct an investigation, make a decision, and issue a check. Insurers were spending a notable amount to issue a payment in the auto claims sector. In some insurance claims, the turnaround time was found to be two weeks or more. The biggest inefficiency in the insurance claims and processing sector is the large volume of partly and fully automated follow-up calls, many of which are unnecessary. Calls that insurance companies claim largely run via IVRs account for the largest number of incoming calls. Despite the IVRs, call levels increase within the insurance industry when claim volumes increase. This means that if the number of routine calls to check the status of a claim could be cut or automated, call center efficiency could be significantly increased. Some insurance providers have managed to reduce claim cycles from claims reporting to payment through the use of technologies. While many insurance carriers have invested heavily in technology, the claims process must become more transparent and effective to truly reach increased efficiency. A study found that a small percentage of respondents had already made major improvements in their core claims system using imaging and workflow tools.

**1.2. Role of AI and Machine Learning in Claims Processing**

AI and machine learning technologies hold transformative potential in the area of insurance claims processing. Currently, many facets of claims and underwriting functions are leveraging these into main operations. AI technologies like RPA are increasingly being used to automate tasks such as data entry. Others, such as predictive modeling, are used to improve certain types of decision-making. In addition to these AI solutions, machine learning can be used to create dynamic models that predict how claims will develop and the expectation of claims performance over time. Additionally, cutting-edge technologies like high-performance computing integrate vast amounts of geospatial and weather data to predict potential claims in regions with catastrophic events. Newer solutions offered by insurtechs provide open-source as well as more advanced technologies that learn from historical data to make more accurate forecasts of ultimate claim values. They have also developed a completely white-labeled claims processing solution providing AI-driven decision support for the entire life cycle of a claim.

Overall, AI has the potential to reduce the time that it takes for the average insurance property claim to be settled, creating appeal for governments, policyholders, and the public at large. Despite this, industry studies indicate a large number of insurers have yet to implement AI solutions, with a significant percentage of European car insurers claiming they had not yet invested in an AI solution in recent years. This is a missed opportunity and the industry should switch to a more data-driven solution for the long-term benefit of its customers. AI and machine learning solutions have already started to be implemented into day-to-day claims processing and management functions. Hosted either through the cloud or via buy-based platforms, these solutions are available to all various sizes, creating a fair and balanced competitive environment. However, knowing where to implement these solutions in an ever-complex claims landscape can be challenging.

**2. Foundations of Machine Learning**

Machine learning can be tough and complex to get your head around if you're not already familiar with how models, algorithms, and training data work. Nevertheless, if you're able to get a good sense of all of this, you are well on your way. At a very basic level, machine learning is comprised of models that take in certain types of data for optimization. In order to improve the model, the machine is provided with a training dataset to work with. This is the process known as learning the weights for the model. The training consists of a risk function or equation that needs to be minimized.

Machine learning can be segmented into three types: supervised, unsupervised, and reinforcement learning. The most used type is supervised learning, and it's used when the system provides the model with an input that has a corresponding output or target associated. Unsupervised learning is used in cases where the model has to organize input data by itself. The aim is to solve problems with limited labeled samples. Lastly, reinforcement learning is used when the system has to take certain actions in order to receive feedback from its environment and learn which feedback is the most profitable to maximize.

**2.1. Basic Concepts and Terminology in Machine Learning**

A dataset is a collection of relevant information that is being considered for whatever reason. The items in a dataset are referred to as instances or samples. These could be individual people, vehicles, activities, businesses, or whatever entities that are relevant to the goal of the analysis. In each instance, there is a collection of attributes or features that have been measured, recorded, or created for that instance. Some of these features may be more relevant than others to the overall goals of the machine learning or data mining activity. The main goal here is to use this dataset to develop a model that is capable of acting on, analyzing, or providing something useful with new or unseen instances. In the context of machine learning, these instances are typically referred to as the training set. In supervised machine learning, associated with each instance in the training set is exactly one relevant piece of information usually referred to as a label. This is like the hidden truth that the machine learning model must be able to deduce from the features associated with the instance. If a particular machine learning algorithm (or indeed any other kind of prediction or pattern discovery tool) is highly adapted to the training data, it is said to be overfit. This means the algorithm may not work very well with new unseen instances because it is very tightly matched to the peculiarities of the instances that were in the training dataset. Crucially, the training set must be as representative as possible of the kinds of things the model is going to be expected to handle. For example, building a model that is supposed to be able to recognize handwritten Arabic characters from the training of only English printed font characters will not be successful because Arabic characters are not in any form present in the set of English printed font characters. It helps to have a good working hypothesis or understanding of what features are going to be important for the goals of the machine learning activity. If this is not known, then it is often the case that the best approach is to throw as many feature candidates into the mix as possible in order to allow an automated feature selection algorithm to deduce what is best. It should be emphasized that this is not a substitute for a decent working hypothesis if someone prefers to do this in a more methodical way.

Different machine learning algorithms have been developed to target different aspects of computing and data analysis. For example, regression models are designed to estimate real continuous values such as the temperature outside at any given time, the time remaining until a particular component wears out, or the expected travel time from a particular location to another, among many others. A common aspect of regression modeling is that, given the same test dataset, two different regression models from two different algorithms (or two identical algorithms with different tuning) will produce the same value for the target variable, assuming all the other steps for creating and training the models have been performed correctly. Conversely, a classification model will typically take as input a list of values for the features and will attempt to return what category these values most likely belong to. The output category could be nominal or ordinal.

### 2.2. Supervised, Unsupervised, and Reinforcement Learning

There are three general categories of machine learning: supervised, unsupervised, and reinforcement learning. The primary distinction across these three areas involves the type of available data and how models are learned. Supervised learning is the most common, where a model learns patterns in labeled datasets, which are referred to as those with known outputs. The purpose of these models is to make predictions given new inputs. Insurance claims processing often involves a number of tasks for which supervised learning is applicable. Unsupervised learning, in contrast, seeks to identify patterns in systems where the data to be modeled lacks known or predefined outputs. Applications in insurance include uncovering hidden groups or communities within labeled data, finding potential colluding parties in a network, or reducing the amount of data presented to an investigator. Finally, reinforcement learning extends supervised learning in a unique way by allowing an agent to make decisions in an environment through trial and error, optimizing these decisions based on occasional rewards and penalties. Use cases for reinforcement learning in insurance are limited to relatively few areas. Each of these machine learning approaches has advantages and limitations in an insurance setting, and choosing the right tool for the task is critical for effective data-centric decision-making.

Reinforcement learning presents a unique approach to learning in the context of a given environment or task. The real world is represented as an environment in which an agent operates and interacts. Both the agent and the environment enter time steps where the agent selects an action from a set of possible actions. The environment then responds to the action with a reward, which indicates the value of a specific action taken, and a new observation indicating the new state of the environment. The purpose is to find a policy that maps the observation to the best action. The goal is to find the policy that maximizes the cumulative future rewards in the long run.

## 3. Applications of Machine Learning in Insurance Claims Processing

Machine learning and artificial intelligence have many applications in the insurance industry. From the underwriting of new policies to customer relationship management, this technology can be used to reduce costs, improve accuracy, and enhance the customer experience. One of the areas where we see these technologies at work to streamline operations is in the processing of insurance claims. This is seen as a slow, tedious, and manual process because of the long list of documents that need to be checked and the judgment involved in approving or denying a claim. The full or partial automation of this process can help reduce costs, reduce the claims handling time, and lead to new business models that can serve customers in ways that were not possible using only manual resources.

There are a few good applications of machine learning in the area of insurance claims processing related to automated claims intake and triage. In the first case, advances in optical character recognition and document understanding can help extract information directly from the documents submitted by the insured without any re-keying by claims handlers. The triage algorithm can be used to check if basic claim prerequisites are met. This also aids insurance companies in messaging to customers that their claims are being handled quickly. The second application is a more advanced underwriting tool used to identify potential fraud. This is often called fraud detection or fraud prediction, but a more accurate name is fraud prevention because the system generally starts the activation workflow for those claims that still need triage or handling by human claims handlers. Claims handling automation finds elements of traditional claims adjudication workflows to digitize. One common digitized workflow decision is estimating the duration and severity of a claim. These algorithms can then push these digitized workflows into operation long before a human processor could do so.

**3.1. Automated Claims Intake and Triage**

A significant portion of resources in claims handling is devoted to claims intake identification, classification into the detailed type of damage, intensity, and triage. Automating this process by employing natural language processing in documents and data extraction allows for frequent and rapid analysis of claims submissions. Additionally, automated systems, through machine learning, can use data patterns to draw conclusions. Automated claims intake systems composed of these technologies have been used to help analyze claims across a variety of insurance marketplaces. Automated claims triage systems equipped with the ability to learn from data have been used on small pockets of commercially set insurance markets for some time at larger insurance organizations. In combination, the two systems can both categorize the nature of a claim and then allocate that claim to the relevant area of the insurance company for further analysis.

Used in isolation, customer-reported data and events could be classified as fraudulent; however, paired with claims submissions, the system can verify the presence of police-related documents or a police report. In this way, technology is able to assimilate and categorize information, thus streamlining and automating these processing categories: Applicability of coverage in claims submissions, Type of damage and description of the events that occurred, and Triaging claims to the relevant area of an insurance company for each line of business. Quicker identification, classification, and assessment of customer-reported claims can improve customer satisfaction and contribute to a better claim duration. The value of automated claims triage systems in customer-reported claims detailed via this methodology has not been modeled. Estimates may assume a reduction in average claim costs with an accompanying lower standard deviation, or a reduction in the mix of claims with a higher average per submission across various states.

Reports suggest that companies using natural language processing and AI/machine learning for systems analytics increase the speed and thoroughness in identifying anomalies and scoring and determining operational and management actions accordingly. As part of an overall AI and customer-centric strategy for accelerating decisions, claims can be assessed at varying levels of detail; some examples include AI-based algorithms: Structured and unstructured claims intake AI assessment per line of business and product family, at the stage upon the intake of customer outreach, policyholder call, chat, or interface analysis; and Final AI-based claims assessment and quick streamlined payment in scheduled waves and/or at lowest cost with the highest customer satisfaction, based on prioritization rules developed for customer service and support at the First Notice of Loss stage and validated by further technology and customer care validation in touchless to low-touch methods for consumer, agent, adjuster, surveyor, and/or provider payments.

### 3.2. Fraud Detection and Prevention

Within continuous protection in the claims process, other uses of machine learning for automation and speed can also be seen in the previous steps of our classification pipeline: fraud detection and prevention. Fraud detection is a prevalent topic in claims and insurance. Various machine learning algorithms are trained on historical data to learn patterns indicative of fraud in claims. The strength of certain machine learning methods is their adaptability to new, changing data, enabling the detection of less obvious fraud signals in a way traditional expert rules do not. The focus of these tools is on fraud detection as an AI strategy for reducing the need for clarification requests as a way of preventing fraud at the outset. In the application of AI-driven claims systems, case studies are presented on the reduction of fraudulent claims as an investment in such systems. One insurance company implementing such a program saw a reduction of 10,000 potentially fraudulent claims worth €124 million, with the AI system requesting further investigation after the next two doctors it was referred to proposed additional tests. In addition to these potential fraud advantages, which help protect the financial interests of the insurer, an ultimate AI strategy in this space needs to offer protection against unfair treatment of clients who are not making a fraudulent claim. One of the other major objectives of the claims process is to provide a fair and equitable experience to all claimants. There is a balance between providing the best possible anti-fraud protection to a customer and facilitating their claim on a reasonable basis. The threshold of what is considered a fraudulent claim and a necessary measure to safeguard against and reduce the payment of claims needs to be carefully outlined. Another challenge raised with insurance companies deploying machine learning solutions for fraud is the question of what is no longer considered 'standard' in auto-adjudication. Are the majority of claims that a 'normal' system assessed for fraud or injury actually bona fide or accurate when it is reassessed by a panel? These questions mean that expert reviewers seek to grasp these borderline cases while insurers confidentially clarify their systems' risk and fairness profile. That the fraudulent claims detection may need to continually evolve is an often-mentioned concern in this space, because typically interacting with a fraud model causes some elements of the population to be deselected at a higher rate. To correct what the model does wrong, the desired outcome is that companies have a consistent system in place to appeal and update incorrect system decisions. Instead, many systematically do not offer an appeals process in the relevant areas of the policy, which is a concern in such a ubiquitous deployment of a system. The often-cited risk in the field is a risk of a mis-train, where day-to-day new data does not feed enough into your system and the model can lose track of what it's trying to detect. Knowing when systems are up-to-date and even 'knowing' a system's risk profile requires evaluation, but again few do the due diligence in their system evaluations needed to confidently implement a model in such a critical case.

### 3.3. Predictive Analytics for Claim Severity and Duration

Predictive analytics can enable us to separate and segregate claims that will take more of our time, talent, and treasure. This could be in terms of dollars, hours taken, or difficulty of resolution. Predictive analytics uses multivariate statistics and machine learning algorithms to weight and score an estimate based on selected factors that can range from

5 to 97 parameters. Each prediction is specifically tailored to the company and claims assignment practice. For example, a recent train wreck where the victims are sent to the emergency room by ambulance will have a lower severity score than an expected hypercar event. Machine learning can forecast claim duration and severity before the claimant walks out of the emergency room and certainly in a few weeks after the event.

AI can give handlers a heads-up about which claim will take longer to resolve. AI can answer the question: why is my claim no longer average in severity or duration? Predictive analytics tells us which claims will take more of our time based on historical outcomes and differentiators. Whatever machine learning model you think might win the challenge, you can replace 'include' with 'similarity and difference,' 'combination of contributing factors,' 'sum uniquely determinant elements,' and 'connected with some combination of parameters derived from historical similar claims selected and averaged by a derivative of the central limit theorem.' All of those statements would be accurate. Carriers are using it for many lines of business to help predict how potential litigation may arise. Some carriers are feeding actionable predictions back to the underwriting team so they can really price to the true exposure. Even more are using it to assist in how to staff their business operations, know which cases may take longer, and understand potential litigation reserves.

**4. Challenges and Ethical Considerations in Implementing AI in Claims Processing**

An underlying promise for deploying AI in claims management is ensuring processing waterproof solutions at scale. However, navigating the insurance sector, claims hold some of the most sensitive, personal, and private information that is only shared under critical conservation on a need-to-know basis. Thus, ethical considerations should never take a back seat. Areas that need to be carefully considered include the legal responsibility towards citizens and customers, biases, and the societal dimension in processing them, transparency, and ultimately trust in both institutions and algorithms. The answer is not a shunning of the risk, but to build the necessary safety nets in place and manage ethical and societal dimensions through technological developments.

Ensuring that biased or prejudiced data is not embedded in machine learning-based algorithms is a critical need. Over the past years, there has been growing attention to the potential bias in processing claims, possibly largely due to the opacity and lack of interpretability of deep learning algorithms, which flag potential ethical, legal, and reputational issues of scaling up such technology too quickly. For insurers, the rewarding advantage of deep learning is its pattern recognition ability, capable of marketing to the individual rather than a demographic of people widely used for calculating risk and setting premiums. The downside to this, from an ethical stance, however, is the reinforcement of discriminatory practices. Are such automated functions enabling a fairer risk management process or unnecessarily increasing low-risk customer premiums? At this point in time, perhaps technological capability has superseded the strides insurance has made in promoting greater inclusiveness in financial services over the last two decades. By failing to design from a valuation principle approach, inclusive values may risk being underperformed.

### 4.1. Data Privacy and Security

Data privacy and security. Considering that insurances daily handle various kinds of sensitive data, among others, health status, family history, medication, and lifestyle, the secure processing of such data is indispensable. However, data breaches associated with AI applications in insurance would certainly affect policyholders' and insureds' trust. Moreover, access to high volumes of personal data at short notice allows a deep insight into the personal life of a data subject. Malicious actors can leverage access to such sensitive data for purposes such as identity theft or social engineering attacks. Last but not least, insurers who have expended significant efforts to ensure the privacy of their clients risk reputation damage, among other concerns. Even under the assumption that appropriate anonymization measures are applied throughout the data aggregation phase, sensitive data is potentially still readable through a special AI model.

In light of the criticalities of the use case described, many insurers take privacy approaches that not only align with legal and regulatory requirements but also seek to establish a good relationship with their clients and manage stakeholders' expectations. In this manner, regulations create a safeguard under which entrepreneurs can act and innovate. This is often cited in business ethical terms regarding the digital economy and big data. Nonetheless, it is not purely a regulation-compliance or ethical issue. The secure processing and discrete handling of complaint data, which requires strict adherence to applicable data protection and information security laws, is also in line with financial supervisory and data protection regulators' requirements for dealing responsibly with this solution. Customer trust is a make-or-break issue in today's data-driven strategy, especially in the insurance sector. It is a matter of trust that a customer would be willing to disclose sensitive data only in a safe and secure environment. Financial services have always been based on pacts of trust, and the currently evolving data-intensive economy reinforces this assumption more than ever.

### 4.2. Bias and Fairness in Machine Learning Algorithms

One of the issues that need to be addressed when using machine learning for fraud detection is the potential for bias in the system. This also applies to machine learning in claims processing. Using machine learning models in an insurance business may result in unintended biases that affect certain groups of customers or create unintended outcomes that affect one group of policyholders more than another. For instance, an AI model trained to identify risky drivers may disproportionately flag certain ethnicities or races as risky drivers, regardless of the fairness of using such a criterion.

Insurers have a duty to ensure that their AI systems are free from sources of bias that would result in unfair differential treatment of customers. It is important for those involved in an AI setup process to ensure that the AI works in the way it was designed to and that the decision-making process is transparent. Skewed data inputs or errors in machine learning systems can lead to biased system outputs, leading to unfair treatment for certain policyholder groups. Not bringing fair outcomes to policyholders caused by biased data or algorithms can reduce confidence in the system and make us less comfortable with the application of machine learning in our business processes. In AI modeling designed to develop internal process optimization, a systems and comprehensive data scientist must understand if data is available to identify a bias-insensitive technique or develop a mechanism to deal with it that is the subject of our research. In addition, the lender must be prepared to consider the risk when implementing the AI model. The pragmatic recommendation would be to use a wider, more diverse dataset to improve performance, incorporating as much as possible a dataset that can include individuals from all walks of life on several continents. This means that if a machine learning system is created, it should be capable of servicing the entire population, with the emphasis on a wide variety of ethnicities. A better approach might be to remove the ethnic column from the database and model without it. If the performance is poor based on fraud, a more comprehensive analysis will clarify.

**5. Future Trends and Opportunities**

The future looks optimistic, with a number of ongoing research and advancements showing promise in the AI and insurance industries. One such area is research advances in natural language processing and image recognition that aim to improve the accuracy of AI in understanding human language and visual data. Advancements like these could help insurance companies accelerate the handling time of claims. Advances like this unlock a variety of opportunities around human/AI interaction designed to increase the velocity of data assessment and expedite the handling time of claims. In the future, AI models should be trained to assess the emotional content of any form of contact from a user and respond with affective or tuned messaging using empathy models.

A second set of opportunities revolves around integrating IoT sensors with AI in order to increase the speed and accuracy of decisions around claim processing and payouts. Innovatively using AI to improve the user's speed in any process will give a competitive edge advantage in the market. This can be especially seen when an AI increases the speed of decisions and therefore payouts in a cash-rich industry such as insurance; paying out faster will improve the positive image and feedback from consumers. The third set of opportunities aims to help insurance companies meet the increasing consumer desires for online service with ever-increasing responses at all times of the day. Making accurate decisions is key as decision accuracy increases to a point and then tails off for input and response time. This is the area that AI and chatbots/virtual assistants will revolutionize and extend to create novel business models. These can be achieved by using chatbots or virtual assistants who can not only provide immediate answers to many of the claimed questions but also will be able to conduct various tasks such as opening and closing claims, booking appointments, or even following up multiple claims at the same time and learning within the chat. Furthermore, these assistants can handle calls during high demand periods or emergency situations and be backed up by a human if the assistant cannot solve the situation. It is the AI mode of the virtual assistant that will allow for the rapid and extended scaling of services to meet consumers' ever-increasing wants at no additional cost. The fourth set of opportunities lies in training real-time data for use in predictive models quickly, as the increased speed to optimum accuracy minimizes potential false positives that can damage the operation of the insurance company. Integrated with chatbots or call centers, the trained predictive model data can assist with reducing the number of accidents and will expedite the payout process. Introducing real-time updates to predictive models will maintain the effectiveness of the model, generating potential differential advantages for the insurance company. Different trained data can be managed depending on individual and group needs, e.g., driving habits in cities or urban areas or the countryside, holidays, or regular commutes. Predictive modeling in this way can lead to differential advantages or can work on economies of scale with larger consumption of the data and greater learning from the predictive model. In summary, we can see that the current trends in chatbot AI and processing of claims are pointing towards a more technologically advanced approach resulting in more relaxing, immediate, multi-channeled refined services with anticipatory methods. These future trends have the advantage of a dynamic element, rather than simply adding more data sets, and do not require an extensive understanding of the income-risk curves.

### 5.1. Advancements in Natural Language Processing and Image Recognition

This report has highlighted some of the fastest-growing technologies that are likely to be part of the insurance landscape in the years to come. While most of the underlying technologies are already in wide use, advances in NLP and image recognition offer huge potential to reduce the time it takes to process claims and provide superior customer service. NLP developments can truly drive better communication between customers and insurers and simpler usage of self-service tools. However, they require greater advances in the field to be safely deployed in everyday usage. Real-time translation, for example, is not yet foolproof, so it's not yet ready for prime time. Just as NLP can improve the speed of checks on claims coming in, image recognition can also slash the time it takes to evaluate simple fire, flood, and window cover claims. Instead of needing human judgment, these tools could help train a decision-support tool for claims handlers to use when they look at what the tech says are the low-risk claims. Technology is mature here, and insurance companies in the P&C space have already deployed similar technology at scale. The German Insurance Company estimates they save 40 cents for every 100 euros of claims handled when they reimpose premiums following small claims. More sophisticated facial recognition technology is available that will enable checking the identified person against ownership and health databases. Insurers can use that to check if the person in the picture is the same as the policyholder or driver on the policy. This can be used both for fraud detection and where insurance companies offer anti-money laundering services. Many benefit payments, such as personal injury claims, are being repurposed by criminal gangs as money laundering channels, and the insurance companies can support stopping this by using biometric technologies. In academia, image processing is an in-demand area of research, and there is significant private investment in this area. Broadly, ongoing research is focused on modeling image quality.

### 5.2. Integration of AI and IoT for Real-Time Data Processing

1. Introduction

5.2 Integration of AI and IoT for Real-Time Data Processing To further assist in improving the claims process, insurance companies are considering integrating artificial intelligence (AI) and the Internet of Things (IoT). AI can process data generated about incidents in real-time and offer functions such as damage assessments for instant resolutions when linked with IoT devices. The network of IoT devices will collect the data from the incidents and showcase what has happened. In the IoT world, these would be sensors in farm fields or connected vehicles where telematics provide data on the status of the vehicles and what the actions were at the time of the incident. By connecting pictures and other data collected by various sources to the IoT dataset, insurance will have the basics of the results needed to service the claim or provide the policyholder with advice in seconds. Using this information, a digital image of the incident gets built—and AI can carry out work like an expert in moments. Overall, the use of real-time IoT data processing enables the development of relationships underpinned by trust as the increased personalization empowers actions and outcomes on a personalized basis.

With the use of AI, IoT data can further enable the following insurance company capabilities: (1) Accurate verification of authenticity; (2) Genuine and total loss notifications; (3) Immediate damage assessments; (4) Damage prediction capabilities; (5) Automatic identification of preferred repairers; (6) Assessment of the risk of fraud; (7) Real-time, AI-mediated claims handling for self-service claims; and (8) Proactive outreach to policyholders in times of need on a personalized basis. Although this is a growing practice, there are already established case studies implementing AI and IoT in the insurance industry. For example, insurance companies use telematics systems to establish personalized motor premiums. The data collected is personalized to the driver and created from trackers, mobile applications, and paired with other sources such as licensing data and unemployment rates. Telematics systems can lower claim frequency rates and improve claim severity when implemented. The end result of accurate premiums and claim reductions led to the consolidation of two of three telematics businesses within the insurance market in 2018. One year later, a separate insurance company integrated AI machine learning and more data sources to expand personalized offerings to its policyholders, including pet insurance, with potential to include healthcare pricing. The technology offering has already been implemented in the auto insurance industry, where partners produced a health monitor for drivers.

**6. Conclusion**

There is no denying that AI has the potential to revolutionize insurance claims processing in various ways. It can bring higher efficiency and automation, faster and more accurate decisions, and a better customer experience. Furthermore, as AI systems are continuously learning from new data and interactions, insurers can quickly adapt to change and always have access to state-of-the-art models for handling claims. However, with great power comes great responsibility, and insurers need to carefully address important ethical considerations when designing, implementing, and governing AI systems. Using AI responsibly and ethically is not only the right thing to do. Demonstrating ethical behavior can also help to build trust and can give insurers an edge in the market by avoiding undesirable attention from regulators and the public. Looking ahead, it is important for the industry to continue innovating with AI and bring about step changes in capabilities. Opportunities abound in further layers of machine learning: continual learning for new technologies; further expertise in unsupervised, transfer, and distillation learning; and innovations in natural language processing and understanding, especially in low data scenarios. The future for claims processing is not just technology; it is behavioral, stemming from the exponents of technology, and heavily informed by the hopes and demystifications of data science. In conclusion, insurers need not delay the advanced technology transformation of claims processing. This demand is timely, as customers increasingly desire access to policy benefits up front—the space between loss and payment. However, we must develop a new balance between surveillance and subscription, data and leading indicators, the code and the ethics, technologies and the values in the world of responsive automation. Errors and bias must be scrutinized locally and globally through transparent technology, insightful experiments, a deepening understanding of the values people hold dear, and accountable governance. If all participants in the industry collaborate and examine each other's work while preserving the compelling value of AI, the gains for the claimant and the insurer in the world of AI will reach new heights.