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Research Article

# Integrating Deep Learning and Machine Learning Algorithms in Insurance Claims Processing: A Study on Enhancing Accuracy, Speed, and Fraud Detection for Policyholders

Sneha Singireddy*

*Software Developer in Testing, snehasingreddy@gmail.com, ORCID ID: 0009-0009-8450-5404

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**ABSTRACT**

This paper focuses on the integration of deep learning and machine learning algorithms in insurance claims processing. The aim is to augment the processing speed and accuracy of reviewing claims, as well as to improve the fraud detection on insurers' (policyholders') side. Utilization of advanced computational techniques as both risk assessment and bad experience are shown having positive influence on the claims events. For the insurance company the speed of analyzing and processing the insurance claims is crucially necessary in assuring the company's reputation, as loyal policyholders may have thought the company abandoned them. From the policyholders aspect, accurate fraud prevention is also very necessary as it happens to help onlookers or channelers to put their interest on the loss, adding those who work in unjustified professions for a living. Exploring both deep learning and machine learning algorithms to analyze and extract information from text and imagery files on the insurance claims, the company as insurer is expected to ease and fasten the verification process. While in the policyholders' side capabilities are enhanced in gauging the validity perpetrators' statement fraud mechanism used. Strengthening the perception of fraud and bad behavior conspire to damage, harm, and defraud companies, employers, policyholders, or third parties. A descriptive fraud, correlating with the damaged fraud specially abuse the misstated damage conditions. Companies are triggered to act as limited as possible with accidents and occurrences of loss on claims events. Insatisfaction, complaint, or anger felt by one party against another party (insuree) is tricked to fulfill their desire to their advantage, by putting their interest in onlookers or channelers to the loss, especially those who work/stay in service or profession which are not justified to be there for their survival. Reliability of events (evidence) can evolve from bad experience or violation of contract parameters, such as redundancy and exaggerated requirements for claim detail (evidence). A risk and bad experience may not directly affect the operational, but can be financially impactful. On the other hand, with the same equally/risk-inclined person, fun experience is expected to be shared, loyal behavior, which will be more profitable.

**Keywords:** Deep learning, machine learning, insurance, claims processing, accuracy, speed, fraud detection.

## 1. Introduction

There are few modern managed-service investment companies in the property damage insurance repair industry, which is specialized in serving carriers and policyholders. Insurance companies and policyholders often need to quickly and accurately process and settle claims. The sooner the insured loss is investigated, the faster a policyholder can restore his or her damaged property. Also, the sooner the claim is settled, the less likely to disputes and fraud. The industry has traditionally used property adjusters to investigate and settle claims. Adjusters are people who come out to the site of the loss in order to assess the situation. Sometimes the process tends to drag on due to additional evaluations, disputes, and widespread fraud. It can take up to a

month to go through the entire process. This impedes the property owner from restoring their damaged property. Meanwhile, it is difficult to staff property adjusters compared to automobiles.
Now disruptive changes are occurring in the insurance claim industry. A reinsurance company commented on an industrial expansion of specific managed-service investment companies in the property damage repair industry. Companies may disrupt the auto insurance industry by using artificial intelligence and the Internet of things. Automation is a focus in driving the future of the insurance industry due to the impacts of big data analysis, the convergence of the property industry and the digital motor repair service, and population trends. Thus it may disrupt the auto insurance industry. For example, like in the healthcare fraud detection field, fraud detection needs to evolve with time and capabilities. It was claimed that traditional machine learning approaches do not flow well with the current ebb of fraudulent activities. These predictions are reinforced by the striking recent increase in more sophisticated and adaptive fraud schemes. The traditional machine learning model's predictive capabilities are based on training on past insights. Such training often results in models that fail to effectively generalize the future complexities of new fraud behaviors. In this light, this research works to enhance and further the spread of the deep learning model's comprehension and applicability in the evolving landscape of health insurance fraud detection practice.Fraudulent practices keep amplified with technological development against vastly increasing fidelity—case in point heading for appropriate quantum calculation—for this reason, hazardous possibilities are more risky than bygone decades. On the other hand, most traditional claims handling systems are no longer able to deliver service rapidly notwithstanding policyholders' endeavor at the expense of handling cost, while service effectiveness is further doubtful.

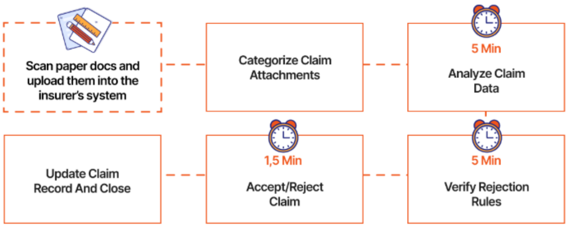


**Fig 1: Machine Learning in Insurance Claims Processing**

## 1.1. Background and Significance

Throughout history, substantial advancements in methods, regulations, and liability coverage substantially transitioned from ancient and medieval periods to the post-Industrial Revolution era and contemporary digital period. After years of contemporary evolution within insurance systems, as well as emerging technologies, claims handling has transitioned substantially. For a long time, calculations, supply chain transfers, and policyholder examinations were manually processed. It may still be labor-thirsty across the modern digital landscape, although it is now expertly automated either by intuitive systems or single specialty software tools. In the digital landscape, nearly all claims actions are automatically processed, although many ledgers still are manually handled, principally when considering supply chain examinations and reimbursement shall be subjected for policyholder report. Nevertheless, consideration should be taken at all times during examination to ensure protection for the right and duty of both insurance taker or provider, therefore claim handling enjoys a crucial status in insurance systems. In today's prospective era post most of the abrupt technological transformation and not yet been coping with insurance systems, improving artificial intelligence or machine learning in conjunction with the insurance industry has won increased popularity. It has been seen to provide not only financial steadiness but also favorableness as regards various policy undertakings, naturally increasing operational effectiveness that results in attaining good services. Nonetheless, such practices are blended directly with risks; protracted latent periods, circumstantial debates, or latent fraud. Indeed, deceitful claims should be detected and downtrodden without tillage, yet alarmingly frequently, they are not revealed at all. This issue may result in the policyholder refusing to extend or cancel the insurance contracts or prosecuting them in related cases on the grounds that they are not being treated properly. The questions and doubts that arise in the minds of the policyholder in this way create a negative perception.

## Equ 1: Speed Enhancement through Parallelization

$$S = \frac{T_{\text{total}}}{T_{\text{parallel}}}$$

Where:

- $S$ is the speedup factor,
- $T_{\text{total}}$ is the total time for sequential processing,
- $T_{\text{parallel}}$ is the time for parallel processing.

### 1.2. Research Objectives

It is well known that most insurance claim processes rely upon certain rules, procedures, and techniques that are performed automatically. The rules and procedures have been designed over time, ranging from recent months to years, with the aim of evaluating personal injury and other claim types, in addition to automating corresponding measures. Despite the automation of the claim process to a certain degree, the final decision on whether the claimant is a victim is taken by humans. It is the human factor in this decision-making process, which is subject to emotions, tiredness, empathy, etc., that the policyholders find sometimes biased. In general, people find alignment and good cause in support of claims in case of lawsuits in almost all issues. However, such opportunities may not be achieved in claim processes, since there is no opportunity for direct defense of the policyholder and the data mainly are the only evidence. Unfortunately, counter-decisions for the policyholder tend to be the rule in such cases, and such a situation damages the strength of the contract, since the good will and expectations of the insured are significantly damaged. Therefore, it is concluded that the decision-making process in the claim evaluation stage must be objective. Understanding the importance of the issue, many approaches have been proposed to deal with insurance fraud. In this study, a hybrid approach is proposed for the claim assessment stage of this issue. Here, Natural Language Processing Techniques (NLP), Deep Learning (DL), and Machine Learning (ML) approaches are integrated. The main objectives of the study can be summarized as follows:

Objective 1: To analyze various Machine Learning and Deep Learning algorithms for insurance fraud and provide accuracy and time efficacy comparison results. The question addresses how the ML and DL algorithm performs for insurance fraud.

Objective 2: To propose a novel Data Preprocessing Operations (DePO) methodology to the insurance claim data set and after that evaluate the insurance fraud using the ML and DL algorithms.

## 2. Literature Review

Deep learning, also known as deep neural learning, is a branch of artificial intelligence. Recently, deep learning has attracted the attention of many researchers in the field of artificial intelligence and has been used in various sectors. It can automatically learn features without explicit knowledge input and be multi-layered. This method has advantages over the traditional machine learning method, which extracts manual features on the multi-dimensional attribute in mathematical methods. As a sub-field of deep learning, sequence deep learning is increasing its impact on many sectors. The sequence of raw data is processed by a neural network, one of the machine learning algorithms used in sequence deep learning. The neural network is an appropriate theoretical foundation where the sequence of data is taken into account. The task sequence of data is one of the most popular research topics in sequence deep learning.

In the insurance sector, the analysis of data is vital. The cost of company claims and also the client's benefit will be deducted when falsified claims are not detected in a timely manner. Using data from a similar year in healthcare, the total cost of falsified claims has been estimated to be significant. An estimated amount of these costs were due to insurance frauds as personal accident insurances. Analyzing an insurance fraud highly unbalanced in the data set is needed. The reason is that the decreased number of falsified cases among the vast amount of data is hard to detect. In the detection of insurance fraud, there are already several approaches for normalizing insurance claims processing. Commonly analytic methods based on hand-crafted graph attributes have been proposed. These methods can solve the problem in isolation or the ability of modeling three or more dependent hetero-relationships of a complex system is limited. Also, the traditional machine learning approach has difficulties in taking into account the complex structure of the claim's graph. On the other hand, the deep neural network method can well model the graph structure of the data.

### 2.1. Deep Learning in Insurance Claims Processing

Recent progress in deep learning methodology, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their hybrids, has established new benchmarks in domains that relate to perception, such as speech recognition, object recognition, and machine translation. Recently, many domains in science, engineering, finance, transportation, and retail, including the automotive industry, have been exploring and adapting Deep Learning techniques. Deep learning has emerged as a powerful methodology for creating underlying representations of complex problems. That's of particular interest when exploring how Deep Learning methodologies can be applied to the problem of insurance claim processing, as claims issues are amongst the most complex within the insurance industry. From this complex nature arises the potential application of Deep Learning methodologies to such issues. Besides, as it can be used to produce unparalleled results when applied to large and often complex datasets. The ability to learn from a dataset of some considerable depth and breadth enables decision-makers within the industry to make more informed decisions and predictions with a high degree of accuracy compared to 'traditional' machine learning approaches. In relation to this, this section follows a general discussion of what Deep Learning is and how it can be utilized to inform and explore complex issues such as those related to claims. Various successful case studies and areas of exploration are also provided to demarcate where these methodologies have been effectively applied within the deep learning community and the insurance industry. Furthermore, consideration is given to the nature of challenges and criticisms which deep learning faces, particularly in the spheres of improper use, theoretical limitations, and data privacy. It remains a domain with continual possibilities for improvement and adaptation to new techniques, theoretical understandings, and dataset robustness. By its conclusion, it is hoped that this will provide a balanced understanding of the scope of Deep Learning within the insurance claims universe.

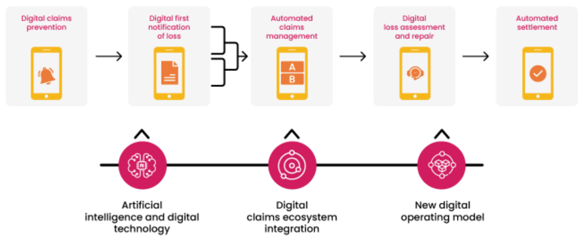


**Fig 2: ML in Insurance Claims Processing**

### 2.2. Machine Learning in Insurance Claims Processing

Machine Learning in Insurance Claims Processing Machine learning algorithms have been widely used in insurance claims processing with claims history data. For instance, to improve operational efficiency, compared decision trees, random forest, gradient boosting, support vector machines, and fully connected neural networks in their ability to forecast the number of open claims. Machine learning (ML) has been used in insurance claims severity prediction and settlement time forecasting on large amounts of data. The greatest importance is given to claims data to identify patterns and anomalies. Claims data owns an extraordinary potential regarding information contained in those data and this information is frequently not visible on a first glance. By now insurance companies follow a policy in which fraudulent behavior is rapidly identified and investigated. Claims data are starting to get a thorough grounding due to advanced techniques such as machine learning. The core of the claims management process is fraud detection and, in this context, the importance of this task came to mind. The management of claims process has become a stringent consideration. There is a growing interest of insurance companies in automated tools and methods to assist in the detection of FC. A classification-based approach designed to assist claim managers on the accuracy of a decision to refer or not refer to an expert claim. Insurers can reject claims or transfer them to a damage expert for further analysis. From a legal perspective, the rejection of a claim is an important decision that has to be taken considering very carefully because a wrong decision could lead to undesirable consequences. The recent statutory provisions provide evidence that the insurance company has made an effort to review the case thoroughly. The customer may file a claim, forcing the insurance company to pay the resulting damages. In order to reduce the risk of this undesirable outcome, it is advisable to have a loss adjusting or an external expert review the claim. This interpretation has encouraged the establishment of common criteria and steps that would also apply in cases where the automatic or semi-automatic evidence-based tools were used to monitor the adhesion of claims to these take-ups. Regarding the FC, the percentage of cases is influenced by the amount declared in the associated claim. In a substantial amount of cases, the damage suffered is close to the deductible, so the customer can inflate the claim in order to obtain a reimbursement. This allows the customer to reduce the economic disadvantage incurred due to their participation in the damages. On the other hand, the company is compelled to pay a higher compensation than the object that has been affected.

## 3. Methodology

This paper integrates deep learning and machine learning algorithms to process claims from policyholders, pointing towards evidence that improved accuracy, improved overall speed, and fraud detection can be achieved by this approach. Researchers analyze existing claims processing by insurance companies and present a framework for enhancing it with the new algorithms. Deep learning algorithms offer a way to both improve and advance basic approaches with higher accuracy than conventional machine learning methods for unstructured and complex data processing. The latter is true for text data included in a written statement provided by policyholders. The combination of deep learning and machine learning algorithms is consequently expected to increase the efficiency of claim handling processes, helping insurance employees to make informed decisions more easily and quickly. Additionally, insurance companies will be better able to identify any potentially fraudulent claims that may arise.

Machine learning was applied to analyzed engineering data to develop a finite failure prediction model. The results showed that machine learning models trained with engineering data provided not only more accurate predictions than classical prediction methods but also identified complex patterns related to engine failures by analyzing a large amount of unstructured data. The classification algorithms tested were ensemble, convolutional neural network, and recurrent neural network. For the development of classifiers using machine learning and deep learning, collected data are preprocessed in different ways before the models are created and trained. Texts are processed differently. The written statements by policyholders are transformed into numerical representations used in a well-known word embedding technique. In the past, this technique has proven to be strong for natural language processing. When a myriad of words is used, it is capable of developing vector representations which maintain the relevant features of those words. Then, using the vectors, the model can determine the semantic similarity or ranking of the words.

### Equ 2: Fraud Detection with Deep Learning

$$L_{\text{CE}} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right]$$

Where:

- $L_{\text{CE}}$ is the cross-entropy loss,
- $y_i$ is the actual label (0 for non-fraud, 1 for fraud) for the $i$-th claim,
- $\hat{y}_i$ is the predicted probability of fraud for the $i$-th claim,
- $N$ is the number of claims.

### 3.1. Data Collection

Data is the key-ingredient for this research. To answer the research questions, the authors study claims data provided by a German insurance company. It is used to construct a labeled data set consisting of historical claims with a binary fraudulent flag. An additional claim data set is given to test the generalization power of the fraud detection model. Furthermore, additional data are naturally joined provided by the insurance company including policy and customer meta-data.

Almost everyone has a car, and if you are one of these people incidents will happen eventually. Car insurance cleans cash for car damages, filling up the tank for a few bucks more, or covering medical treatments; it's basically the bullet proof vest for your automobile. Insurance companies manage a great deal of data associated with the signed contracts. Acknowledging the high rate of incidents and fraudulent activities that usually accompany the settlement process, these companies must dispose of accurate and effective mechanisms to deal with the disputes. To remain in the game, it is essential that best practices continue to evolve, and to ensure that the set of induction prospects are intelligent, precise and quick.

With the growth of big data and unintentional fixation on the internet, there has been a perceptive rise in the number of fraud cases which can be originated by the abuse of these assets. The measureless and confusing nature of this data delimits the grasp of a particular horoscope in regard to techniques or tools to work effectively in this field. Active studies commenced efforts towards the reconciliation of the uncertainties that lie upon these intersections. This article discusses enhancing the accurateness, velocity, and fraud detection of the settlements imposed by a mutual insurance partner business with a German Automobile Association. The questions were answered by taking advantage of deep learning and machine learning (ML) approaches. First, a set of factors motivating the fiction of this conception of the problem is laid out. Later, four stages are accordingly elaborated by which these questions were answered. The primary focus lies in the explanation of the outcomes from which high assurance answers were conducted.


**Fig 3: Data Collection**

### 3.2. Data Preprocessing

Data preprocessing includes a wide range of important steps including selecting data, cleaning data, and preprocessing data. These steps are crucial for transforming raw data into a format that is valuable for analysis. This part of the data mining analysis process is often underappreciated and is overlooked by analysts. However, this part is vital and should never be dismissed. The results obtained after analysis often depend on the quality of the preprocessing tasks. Data cleaning, for instance, involves many small but important steps, such as handling missing values, handling duplicates, and handling outliers. Inadequate data cleaning can negatively affect the results and can lead to inaccurate results.

Data preprocessing manipulates raw data into a more understandable format and enhances the quality of the data. The crucial steps of data preprocessing used in this study are cleaning, normalization, and structuring. Cleaning data is mainly purposed to remove missing values, and normalization refers to standardizing data to be between 0 and 1. Structuring is employed to ensure every row should contain the same attributes. Preprocessing is a key preliminary step in analyzing and separating data into valuable and useful information. Data preprocessing is a critical step for successful data mining. This step is particularly important since the results of data mining algorithms are highly affected by the quality and nature of the data. It may be impossible to use an unprepared raw data set for data mining since the data set often includes missing, inconsistent, or incompatible data. Data preprocessing includes cleaning, enhancing, integrating, and reducing the initial data. The data which is preprocessed by these methods significantly improves the efficiency of the data mining models. Major techniques applied in the study to prepare data are cleaning, normalization, and structuring. The missing value is to eliminate the rows which have missing values, normalization is to rescale the value within 0-1, and structuring is to ensure that all the rows must have the exact same attributes usually requires a binning process. Feature selection and extraction are applied to removing irrelevant attributes and combining multiple related ones to make the analysis results more significant and accurate. Preprocessing is often an intricate process that can involve multiple steps and apply different techniques. Methods for data transformation such as scaling and encoding that adapts the data for machine learning analysis are discussed. The quality and type of data largely determine the success of an analysis. It is shown through multiple experiments that high-quality data leads to high-performing algorithms. Alternatively, low-quality data can skew results and render learning algorithms useless.

## 4. Results

**Introduction:** The insurance sector is one of the largest contributors to the world economy. Insurance plays an important role for both policyholders and the economy, providing financial protection against uncertainty. Policyholders spend a fixed premium and buy an insurance policy from insurance companies. To protect policyholders from more uncertain events, they proceed with insurance claims. The claims processing process is crucial to the successful operation of the insurance industry. Before settling a claim, the company investigates the claim request. In the broadest context, processing a claim involves assessment and cash payment. Many sophisticated methodologies have been developed to improve this claims processing process. In both health and life insurance, the same methodologies cannot be applied to the other claim solutions.

Although insurance companies may be using multiple methods for claim processing, the accuracy of the method used is less and takes more time, which would be a disadvantage for policyholders. To address these insurance company challenges, a novel method for claims processing is proposed in the current work. This unique methodology combines traditional machine learning algorithms and state-of-the-art deep learning algorithms. The machine learning algorithms used in this work are Random Forest, Decision Tree, and Extra Tree, and this methodology integrates the Long Short-term Memory Neural Network for deep learning. After extraction, this unique mixture of machine learning and deep learning algorithms provides a technical platform for the claims processing process of the insurance company and will estimate the accuracy and processing time of the claim solution.

### 4.1. Accuracy Improvement

In evaluating insurance claims, the workflow needs to be accurate, ensure a faster evaluation process, have high accuracy for the policyholder, and detect coverage accurately. Traditional ways usually follow simple programming methodologies or use historical data based on the rule, and estimates are not always accurate. Claims assessment is the most important aspect of an insurance firm in terms of delivery speed and fortification. To fulfill this need, advanced data knowledge and artificial intelligence algorithms are implemented by integrating deep learning and machine learning methodologies. To assess the impact, attributes results were grounded on the claim assessment dataset of a motor vehicle insurance company. In terms of accuracy, precision, and parameters set forth, pertinence is ensured, and pros and cons are scientifically examined. Research also gives subtle weight to rule interpretations, providing a balanced comparison approach among adherence, speed, accuracy, and coverage.

In accordance with the aforementioned assessments, the accuracy status of claim evaluation adjusts to the accuracy benchmark upon acceptance of policies. All of a sudden, the application aspect can easily be discovered. For the three major KPIs, the impedance of the application is also parallel and of lesser value. A more leakage is found in the cumulative intelligence after a deeper, more profound assessment. The accuracy of the model granted is of enormous significance and has a substantial influence on the ongoing application of the model. It mainly underscores the difference of accuracy value between the two models. Trends throughout the same time point and period are more about a stable accuracy level.

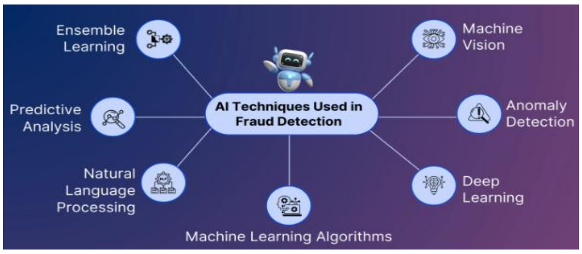


**Fig 4: Improve Fraud Detection Accuracy**

### 4.2. Speed Enhancement

The enhancement in processing speed for claims using the machine learning and deep learning algorithms is considerable. The speed increased by using 3 machine learning algorithms and one deep learning framework. This is explained with the help of the comparative analysis on two databases, one giving 6 highly optimized non-learned models as the output and the other the ensemble of 6 highly optimized learned and pre-trained models as the output. The first base uses random forest, genetic programming, and support vector machines. Their implementations are characterized by execution times. The 5-minute reduction in the cycle of claim prosecution becomes an accumulation of minor savings in the algorithm time, model pre-preparation time, database fetch time, and annual model parameters software save time, utilization of 8 cloned pre-trained models, and averaging the weekly received preliminary claims, thus enabling the real-time option and fully implemented logic. Random forest, genetic programming, Extreme Gradient Boosting, Neural Network, and the deep learning Long Short Term Memory algorithm are the 5 employed models. Currently, they analyze the claims passing their regulatory checking directly from the popular email management provider to the internal receiving-replaying software, converting it into the database format request, and providing the record of the case. In general, the natural language processing tool eliminates stops and stems words to restrict the tally of unique words contributing to the model to 37080 in all each week. Deep Learning (DL) as a subset of Machine Learning (ML) dictates that comprehensive systems learn from information instead of having to be distinctly coded for each eventuality. Claims are a part of the spoken and/or written statement of policyholders that initiates the claims process from the insurance carrier. The claim cycle can be split into the three macro parts to streamline the process regardless of the claim case nature: taking notice and franchise regulatory checking, successive in-depth analysis, and prosecution, and satisfaction of the decision concerning the on-demand and the acceptance/rejection of the case, typically performed by the rules-based and learned model and legal personnel, and the preparation and distribution of the corresponding paperwork. RPA experts can strive to optimize the timely routine by sticking to the general principles of efficiency and automation, trim steps, decrease movements, speed up the involved software, perform parallel tasks, aim for a 4-hour cycle to leave time for potential manual study and changes, follow up with the underwriters, use available public holidays, introduce queueing, and so on. The fast response here is an improved rural claim process that involves some measures including that the examining checks have been automated, which ensures that documentation errors are captured and reported on the day of delivery; failures in pictures required for in-depth inspection are imaged and examined on the same day, reformulation proofs are reviewed in near real-time.

## 5. Discussion

A significant change in operations for the insurance company has occurred. Improvements in both speed of processing and accuracy have been reported, with benefits not just for the insurer but also seen to be in the interests of transparency with respect to the policyholder. Three research questions are addressed and measuring concept drift is shown to be relevant but challenging. Notable findings also include the comparative outcomes of machine learning and deep learning attempts and the suggestion of an ensemble model. With a focus on insurance claims processing, a field inhabited by over a million insurance workers and an outcome source of nearly $4 trillion in invoices, the potential for improved operational notion is seen as wide ranging. It is argued that this approach could be particularly useful implemented in fields where workers undertake high volumes with potentially low variance tasks but where significant expertise is necessary. To some extent, models of insurance claims processing could take what results show to be a way of the direction and future work is equally likely to be undertaken by researchers or robots. Large portions of white-collar industries could be the subject of dramatic changes in the same way that a vast number of manual workers have already fallen to the machines. Although there is potential for job creation within a new industry based upon the requisite design, maintenance and repair of new systems, there remains the threatening possibility of mass unemployment. For insurers, an opportunity to rake yet more excessive profits once the initial deployment costs have been absorbed, but the perception of policyholders in the processing of theirs and others' claims as being rendered by inordinately, and increasingly impenetrable black box processes, less favourable. The technology and analytic techniques may be taking early steps towards something considered. Rethinking as the robots state, but a reflection on broader macroeconomic consequences urges a more circumspect embrace. GDP might not be sufficient. Checks and balances are required so as to ensure that automation benefits the many over the few.

### Equ 3: Efficiency in Claim Approval

$$R_{\text{process}} = \frac{N_{\text{claims}}}{T_{\text{process}}}$$

Where:

- $R_{\text{process}}$ is the claims processing rate,
- $N_{\text{claims}}$ is the number of claims processed,
- $T_{\text{process}}$ is the total time taken to process the claims.

### 5.1. Implications of Findings

From an operations perspective, insurers continually face the challenge of finding ways to enhance the accuracy of insurance claims while increasing the speed of settlements. The need for accuracy is driven by the need to reserve, or set aside, the exact funds needed to cover a claim. Settlements represent an insurer's insurance contract, and some policies might require insurers to settle claims within a certain period. This study sought to explore the effectiveness of integrating deep learning and machine learning in addressing these operational concerns of insurers. Generally, deep learning models which focus on learning representations of data perform more efficiently than the conventional machine learning models on claims processing estimates, particularly on the accuracy of the estimated claims reserves compared to the settlement amounts. Insurer is therefore recommended to integrate deep learning and machine learning models to internal workflows, if not already doing so. Internally developing or procuring native deep learning models can be advantageous in the long run; otherwise, contemporary cloud-based models could be used. Efficiency through automation has also been a focus, with touch-tone systems and chatbots making it hard to distinguish between a machine and a human. The sharing economy, made up of decentralized peer-to-peer online platforms, lures customers away with efficient and responsive service. An argument could be made that the anticipated switch of non-economical and frequently contactable insurance policies to 24/7 online intelligent bots would be just a byproduct of this new online service environment, not necessarily a discretion of deep learning and machine learning. Nevertheless, it is important for insurers adopting this technological advancement to consider the awaiting innovation in the competing markets as well as regulatory restrictions that protect customers who seem to be left behind by the latest innovation in digital markets. At this stage, mature cloud-based models could be used, especially if the task in focus is not the insurer's core business. Insurers may also consider the strategies of potential and niche product differentiation for successful adoption. To reassure policyholders, education on the responsible use of data and issues of algorithm transparency and fairness should be provided.

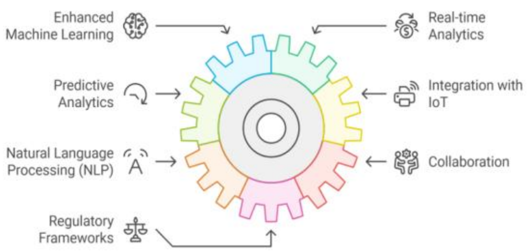


**Fig 5: Implications of Findings**

### 5.2. Limitations and Future Research Directions

As with any study, there are several limitations to note in this research. The most prominent limitation was the quality and type of data received – this study is benchmarked using unique data sources, which are needed for the nature of the processed script and records. Policyholder insights are specifically focused as a first test subject, as well as an evaluated set of estimates and results gathered from insurance companies, insurance adjusters, insurance auditors, and insurance actuaries. There is a data management interface that exists in-between coding, submitting and enforcing BERT, and acquiring and formatting list data. Fraudulent claim probabilities are pre-computed for the policyholder's script, change, and fitted of the rates and assessed claims overall. The model and technical expertise to prepare and generate a new set of policyholder and evaluation data was not procured; nevertheless, the post-processing or the use of fraud detection algorithms may still invalidate the current set of claims. A study was put together on the scripts and fitted rates for the policyholder data set as personally submitted and there was no way to interact with the dispute or claims prepared for individual records that were submitted. An additional data set was submitted, then estimated by the fraudulent claims computer algorithm written. The results of this document were included to be considered as a base case and benchmark for similar claimants and policyholders. This study's recommendations, which are the practices and estimation results, are intended as a future document for an appropriate field evaluator in the insurance industry to keep in mind and prevent possible risks and struggles in making and providing record or script formats. Future research into the design or algorithm used to procure a set of estimates is recommended and important – deep learning and machine learning algorithms are not immune to bias and/or error. If no access to a policyholder or adjuster, the estimates and claims prepared for review cannot uncover fraud, regardless if the dispute was unjustly low in its calculation. Similarly, the clones written and submitted cannot improve a low fit of the dispute, and are not expected to catch a fraudulently high review. Given the data privacy issues, the use of personal or a more exhaustive treatment of claim data is not considered; however, the work is still interesting and relevant for policyholders. It considers the commercial insurance industry, where P&C and large-scale policy premiums necessitate the issuance of commercial insurance policies. Reporting and analyzing an underlying claim – on which data is treatment adjusted – is possible outside the scope of 24 companies, auditors, or adjusters considered. Such a consideration may also reach ambiguous or conflicting results – while biased, no commercial interest on the sides of policyholder and insurer. Furthermore, it is in the industry interest not to document the fraud strategy.

## 6. Conclusion

This study shows how deep learning can be integrated with the existing machine learning algorithms in the insurance sector. Particularly, the insurance claim process will be optimized in terms of increasing the speed and accuracy to meet policyholders' point of view, and as an enhancement to fraud detection. Therefore, deep learning algorithms are implemented. As a deeper version of machine learning, the deep learning method has a better use in data classification and identification than machine learning. The comparison of deep learning and machine learning in this study can be optimized. This approach sees how deep learning affects processing time and accuracy in processing large amounts of data. By then, it will be used to infer the effect of deep learning on fraud detection. Deep learning networks are created with convolutional neural network models and recurrent neural network models. Both models are generated after the size of their respective architecture has been optimized using coverage variables that are frequently used in studies. The data shows the number of claims made in Indonesia. The data claim amounts are obtained from a black box description and attributes. The number of claims made in Indonesia per month is estimated to be data. It is very important for the Company to have reliable and qualified work procedures to take measures towards the policyholder when a claim proceeds. The Company wishes to make improvements upon the claim settlement process to detect fraud. Most of the time this is the mistake of the claim officers who don't pay attention to the name of the letter.

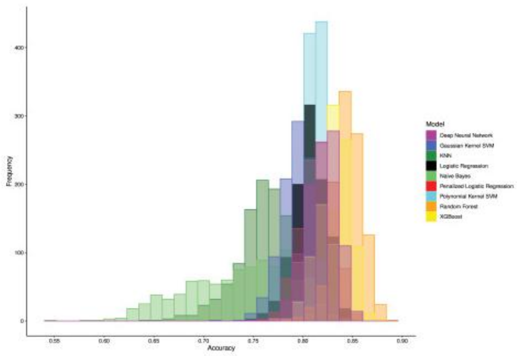


**Fig : Fraud prediction in property insurance**

### 6.1. Future Trends

Deep and Machine Learning, Popular Trends, and Insurance - Claims Processing The chaotic situation that the world has plunged into as a result of actions taken by people; or changes regarding natural law, the Earth, or atmosphere; and etc, in other words, unprecedented-to-date global scale issues, has outlined the urgency of today's insurance sector, where sustainable economic development plays a key role for companies, managers and policy holders. Beyond this, privacy, data and asset protection have rapidly emerged as the most important issues after economic concerns. Since the 1980s, a 70% increase in natural disasters and shadows of anthropogenic events on weather have threatened lives, the continuation of life in particular regions, health and the ability to live continues to remain in question. As a catcher in the rye concept, a transition has been made to a more conservative, risk-sensitive, and technology- and data-based insurance policy in order to secure policy sales, to be an umbrella in economic terms for the accidents that may be faced, and to serve a significant moral, social responsibility for many people who are prone to unconditional disasters. On the other hand, since the start of 2020, online and digital health applications have rapidly emerged due to extraordinary situations similar to a process of rapid shift button controlled cold start under the effects of a global epidemic, which has enabled the preparation of a broad ground for this. The negative and undesirable conditions in which they find themselves in everyday life due to this and the developments to come accelerate the migration to digital platforms even faster.

## 7. References

[1] Dheeraj Kumar Dukhiram Pal, Jenie London, Ajay Aakula, & Subrahmanyasarma Chitta. (2022). Implementing TOGAF for Large-Scale Healthcare Systems Integration. Internet of Things and Edge Computing Journal, 2(1), 55–102. Retrieved from https://thesciencebrigade.com/iotecj/article/view/464

[2] Avinash Pamisetty. (2022). Enhancing Cloudnative Applications WITH Ai AND Ml: A Multicloud Strategy FOR Secure AND Scalable Business Operations. Migration Letters, 19(6), 1268–1284. Retrieved from https://migrationletters.com/index.php/ml/article/view/11696

[3] Balaji Adusupalli. (2022). The Impact of Regulatory Technology (RegTech) on Corporate Compliance: A Study on Automation, AI, and Blockchain in Financial Reporting. Mathematical Statistician and Engineering Applications, 71(4), 16696–16710. Retrieved from https://philstat.org/index.php/MSEA/article/view/2960

[4] Chakilam, C. (2022). Generative AI-Driven Frameworks for Streamlining Patient Education and Treatment Logistics in Complex Healthcare Ecosystems. Kurdish Studies. Green Publication. https://doi. org/10.53555/ks. v10i2, 3719.
[5] Sondinti, L.R.K., & Pandugula, C. (2023). The Convergence of Artificial Intelligence and Machine Learning in Credit Card Fraud Detection: A Comprehensive Study on Emerging Trends and Advanced Algorithmic Techniques. International Journal of Finance (IJFIN), 36(6), 10–25.
[6] Koppolu, H. K. R. Deep Learning and Agentic AI for Automated Payment Fraud Detection: Enhancing Merchant Services Through Predictive Intelligence.
[7] Sriram, H. K., & Seenu, A. (2023). Generative AI-Driven Automation in Integrated Payment Solutions: Transforming Financial Transactions with Neural Network-Enabled Insights. International Journal of Finance (IJFIN), 36(6), 70-95.
[7] Sriram, H. K., & Seenu, A. (2023). Generative AI-Driven Automation in Integrated Payment Solutions: Transforming Financial Transactions with Neural Network-Enabled Insights. International Journal of Finance (IJFIN), 36(6), 70-95.
[8] Burugulla, J. K. R. (2022). The Role of Cloud Computing in Revolutionizing Business Banking Services: A Case Study on American Express's Digital Financial Ecosystem. Kurdish Studies. Green Publication. https://doi. org/10.53555/ks. v10i2, 3720.
[9] Chava, K. (2023). Revolutionizing Patient Outcomes with AI-Powered Generative Models: A New Paradigm in Specialty Pharmacy and Automated Distribution Systems. Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi. org/10.53555/jrtdd. v6i10s (2), 3448.
[10] Reddy, R., Yasmeen, Z., Maguluri, K. K., & Ganesh, P. (2023). Impact of AI-Powered Health Insurance Discounts and Wellness Programs on Member Engagement and Retention. Letters in High Energy Physics, 2023.
[11] Challa, K. (2023). Transforming Travel Benefits through Generative AI: A Machine Learning Perspective on Enhancing Personalized Consumer Experiences. Educational Administration: Theory and Practice. Green Publication. https://doi. org/10.53555/kuey. v29i4, 9241.
[12] Sondinti, K., & Reddy, L. (2023). Optimizing Real-Time Data Processing: Edge and Cloud Computing Integration for Low-Latency Applications in Smart Cities. Available at SSRN 5122027.
[13] Malempati, M., & Rani, P. S. Autonomous AI Ecosystems for Seamless Digital Transactions: Exploring Neural Network-Enhanced Predictive Payment Models.
[14] Pallav Kumar Kaulwar. (2023). Tax Optimization and Compliance in Global Business Operations: Analyzing the Challenges and Opportunities of International Taxation Policies and Transfer Pricing. International Journal of Finance (IJFIN) - ABDC Journal Quality List, 36(6), 150-181.
[15] Nuka, S. T. (2023). Generative AI for Procedural Efficiency in Interventional Radiology and Vascular Access: Automating Diagnostics and Enhancing Treatment Planning. Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi. org/10.53555/jrtdd. v6i10s (2), 3449.
[16] Kannan, S., & Saradhi, K. S. Generative AI in Technical Support Systems: Enhancing Problem Resolution Efficiency Through AIDriven Learning and Adaptation Models.
[17] Kalisetty, S. (2023). The Role of Circular Supply Chains in Achieving Sustainability Goals: A 2023 Perspective on Recycling, Reuse, and Resource Optimization. Reuse, and Resource Optimization (June 15, 2023).
[18] Challa, S. R. Diversification in Investment Portfolios: Evaluating the Performance of Mutual Funds, ETFs, and Fixed Income Securities in Volatile Markets.
[19] Paleti, S. Transforming Money Transfers and Financial Inclusion: The Impact of AI-Powered Risk Mitigation and Deep Learning-Based Fraud Prevention in Cross-Border Transactions.
[20] Ganti, V. K. A. T., Pandugula, C., Polineni, T. N. S., & Mallesham, G. Transforming Sports Medicine with Deep Learning and Generative AI: Personalized Rehabilitation Protocols and Injury Prevention Strategies for Professional Athletes.
[21] Vamsee Pamisetty. (2023). Optimizing Public Service Delivery through AI and ML Driven Predictive Analytics: A Case Study on Taxation, Unclaimed Property, and Vendor Services. International Journal of Finance (IJFIN) - ABDC Journal Quality List, 36(6), 124-149.
[22] Komaragiri, V. B. The Role of Generative AI in Proactive Community Engagement: Developing Scalable Models for Enhancing Social Responsibility through Technological Innovations.
[23] Ganti, V. K. A. T., Edward, A., Subhash, T. N., & Polineni, N. A. (2023). AI-Enhanced Chatbots for Real-Time Symptom Analysis and Triage in Telehealth Services.
[24] Annapareddy, V. N., & Seenu, A. (2023). Generative AI in Predictive Maintenance and Performance Enhancement of Solar Battery Storage Systems. Predictive Maintenance and Performance Enhancement of Solar Battery Storage Systems (December 30, 2023).
[25] Chandrashekar Pandugula, & Zakera Yasmeen. (2023). Exploring Advanced Cybersecurity Mechanisms for Attack Prevention in Cloud-Based Retail Ecosystems. Journal for ReAttach Therapy and Developmental Diversities, 6(10s(2), 1704–1714. https://doi.org/10.53555/jrtdd.v6i10s(2).3420
[26] R. Daruvuri and K. Patibandla, "Enhancing data security and privacy in edge computing: A comprehensive review of key technologies and future directions," International Journal of Research in Electronics and Computer Engineering, vol. 11, no. 1, pp. 77-88, 2023.

[27] Vijay Kartik Sikha (2023) The SRE Playbook: Multi-Cloud Observability, Security, and Automation. SRC/JAICC-136. Journal of Artificial Intelligence & Cloud Computing DOI: doi.org/10.47363/JAICC/2023(2)E136
[28] Vankayalapati, R. K. (2023). High-Speed Storage in AI Systems: Unlocking Real-Time Analytics in Cloud-Integrated Frameworks. Available at SSRN 5094309.
[29] Chandrashekar Pandugula, & Zakera Yasmeen. (2023). Exploring Advanced Cybersecurity Mechanisms for Attack Prevention in Cloud-Based Retail Ecosystems. Journal for ReAttach Therapy and Developmental Diversities, 6(10s(2), 1704–1714. https://doi.org/10.53555/jrtdd.v6i10s(2).3420
[30] Koppolu, H. K. R. (2022). Advancing Customer Experience Personalization with AI-Driven Data Engineering: Leveraging Deep Learning for Real-Time Customer Interaction. In Kurdish Studies. Green Publication. https://doi.org/10.53555/ks.v10i2.3736
[31] Sriram, H. K. (2022). AI Neural Networks In Credit Risk Assessment: Redefining Consumer Credit Monitoring And Fraud Protection Through Generative AI Techniques. Migration Letters, 19(6), 1017-1032.
[32] Chava, K., & Rani, D. P. S. (2023). Generative Neural Models in Healthcare Sampling: Leveraging AI-ML Synergies for Precision-Driven Solutions in Logistics and Fulfillment. Frontiers in Health Informa (6933-6952).
[33] Reddy, R., Maguluri, K. K., Yasmeen, Z., Mandala, G., & Dileep, V. (2023). Intelligent Healthcare Systems: Harnessing Ai and Ml To Revolutionize Patient Care And Clinical Decision-Making. International Journal of Applied Engineering & Technology, 5(4).
[34] Challa, K. Dynamic Neural Network Architectures for Real-Time Fraud Detection in Digital Payment Systems Using Machine Learning and Generative AI.
[35] Sondinti, K., & Reddy, L. (2023). The Socioeconomic Impacts of Financial Literacy Programs on Credit Card Utilization and Debt Management among Millennials and Gen Z Consumers. Available at SSRN 5122023.
[36] Malempati, M. (2022). Machine Learning and Generative Neural Networks in Adaptive Risk Management: Pioneering Secure Financial Frameworks. Kurdish Studies. Green Publication. https://doi.org/10.53555/ks. v10i2, 3718.
[37] Pallav Kumar Kaulwar. (2022). The Role of Digital Transformation in Financial Audit and Assurance: Leveraging AI and Blockchain for Enhanced Transparency and Accuracy. Mathematical Statistician and Engineering Applications, 71(4), 16679–16695. Retrieved from https://philstat.org/index.php/MSEA/article/view/2959
[38] Nuka, S. T. (2022). The Role of AI Driven Clinical Research in Medical Device Development: A Data Driven Approach to Regulatory Compliance and Quality Assurance. Global Journal of Medical Case Reports, 2(1), 1275.
[39] Kannan, S. The Convergence of AI, Machine Learning, and Neural Networks in Precision Agriculture: Generative AI as a Catalyst for Future Food Systems.
[40] Kalisetty, S., Vankayalapati, R. K., Reddy, L., Sondinti, K., & Valiki, S. (2022). AI-Native Cloud Platforms: Redefining Scalability and Flexibility in Artificial Intelligence Workflows. Linguistic and Philosophical Investigations, 21(1), 1-15.
[41] Challa, S. R. (2023). The Role of Artificial Intelligence in Wealth Advisory: Enhancing Personalized Investment Strategies Through DataDriven Decision Making. International Journal of Finance (IJFIN), 36(6), 26-46.
[42] Venkata Krishna Azith Teja Ganti, Chandrashekar Pandugula,Tulasi Naga Subhash Polineni, Goli Mallesham (2023) Exploring the Intersection of Bioethics and AI-Driven Clinical Decision-Making: Navigating the Ethical Challenges of Deep Learning Applications in Personalized Medicine and Experimental Treatments. Journal of Material Sciences & Manufacturing Research. SRC/JMSMR-230. DOI: doi.org/10.47363/JMSMR/2023(4)192
[43] Polineni, T. N. S., abhireddy, N., & Yasmeen, Z. (2023). AI-Powered Predictive Systems for Managing Epidemic Spread in High-Density Populations. In Journal for ReAttach Therapy and Developmental Diversities. Green Publication. https://doi.org/10.53555/jrtdd.v6i10s(2).3374
[44] Ravi Kumar Vankayalapati , Venkata Krishna Azith Teja Ganti. (2022). AI-Driven Decision Support Systems: The Role Of High-Speed Storage And Cloud Integration In Business Insights. Migration Letters, 19(S8), 1871–1886. Retrieved from https://migrationletters.com/index.php/ml/article/view/11596
[45] Pandugula, C., & Nampalli, R. C. R. Optimizing Retail Performance: Cloud-Enabled Big Data Strategies for Enhanced Consumer Insights.
[46] Chava, K. (2022). Redefining Pharmaceutical Distribution With AI-Infused Neural Networks: Generative AI Applications In Predictive Compliance And Operational Efficiency. Migration Letters, 19, 1905-1917.
[47] Maguluri, K. K., & Ganti, V. K. A. T. (2019). Predictive Analytics in Biologics: Improving Production Outcomes Using Big Data.
[48] Kothapalli Sondinti, L. R., & Syed, S. (2022). The Impact of Instant Credit Card Issuance and Personalized Financial Solutions on Enhancing Customer Experience in the Digital Banking Era. Universal Journal of Finance and Economics, 1(1), 1223. Retrieved from https://www.scipublications.com/journal/index.php/ujfe/article/view/1223

[49] Malempati, M. (2022). AI Neural Network Architectures For Personalized Payment Systems: Exploring Machine Learning's Role In Real-Time Consumer Insights. Migration Letters, 19(S8), 1934-1948.
[50] Sai Teja Nuka (2023) A Novel Hybrid Algorithm Combining Neural Networks And Genetic Programming For Cloud Resource Management. Frontiers in Health Informa 6953-6971
[51] Kalisetty, S., & Ganti, V. K. A. T. (2019). Transforming the Retail Landscape: Srinivas's Vision for Integrating Advanced Technologies in Supply Chain Efficiency and Customer Experience. Online Journal of Materials Science, 1, 1254.
[52] Ganti, V. K. A. T., Pandugula, C., Polineni, T. N. S., & Mallesham, G. Transforming Sports Medicine with Deep Learning and Generative AI: Personalized Rehabilitation Protocols and Injury Prevention Strategies for Professional Athletes.
[53] Komaragiri, V. B. (2022). AI-Driven Maintenance Algorithms For Intelligent Network Systems: Leveraging Neural Networks To Predict And Optimize Performance In Dynamic Environments. Migration Letters, 19, 1949-1964.
[56] Ganti, V. K. A. T., & Valiki, S. (2022). Leveraging Neural Networks for Real-Time Blood Analysis in Critical Care Units. In KURDISH. Green Publication. https://doi.org/10.53555/ks.v10i2.3642
[57] Pandugula, C., & Yasmeen, Z. (2019). A Comprehensive Study of Proactive Cybersecurity Models in Cloud-Driven Retail Technology Architectures. Universal Journal of Computer Sciences and Communications, 1(1), 1253. Retrieved from https://www.scipublications.com/journal/index.php/ujcsc/article/view/1253
[58] Sikha, V. K. 2020. Ease of Building Omni-Channel Customer Care Services with Cloud-Based Telephony Services & AI. Zenodo. https://doi.org/10.5281/ZENODO.14662553.
[60] Vijay Kartik Sikha, & Satyaveda Somepalli. 2023. Cybersecurity in Utilities: Protecting Critical Infrastructure from Emerging Threats. Journal of Scientific and Engineering Research. https://doi.org/10.5281/ZENODO.13758848.
[61] Sikha, V. K., & Siramgari, D. 2023, March 30. Finops Practice Accelerating Innovation on Public Cloud. Zenodo. https://doi.org/10.5281/ZENODO.14752447.
[62] Challa, S. R. (2022). Optimizing Retirement Planning Strategies: A Comparative Analysis of Traditional, Roth, and Rollover IRAs in LongTerm Wealth Management. Universal Journal of Finance and Economics, 2(1), 1276.
[63] From Precision Medicine to Digital Agility: Subash's Role in Transforming Complex Challenges into Scalable Industry Solutions. (2023). In Nanotechnology Perceptions (pp. 1–18). Rotherham Press. https://doi.org/10.62441/nano-ntp.vi.4677
[64] Komaragiri, V. B., & Edward, A. (2022). AI-Driven Vulnerability Management and Automated Threat Mitigation. International Journal of Scientific Research and Management (IJSRM), 10(10), 981-998.
[65] Ganti, V. K. A. T. (2019). Data Engineering Frameworks for Optimizing Community Health Surveillance Systems. Global Journal of Medical Case Reports, 1, 1255.
[66] Yasmeen, Z. (2019). The Role of Neural Networks in Advancing Wearable Healthcare Technology Analytics.
[67] Vankayalapati, R. K. (2020). AI-Driven Decision Support Systems: The Role Of High-Speed Storage And Cloud Integration In Business Insights. Available at SSRN 5103815.
[68] Puli, V. O. R., & Maguluri, K. K. (2022). Deep Learning Applications In Materials Management For Pharmaceutical Supply Chains. Migration Letters, 19(6), 1144-1158.
[69] Sikha, V. K., Siramgari, D., Ganesan, P., & Somepalli, S. 2021, December 30. Enhancing Energy Efficiency in Cloud Computing Operations Through Artificial Intelligence. Zenodo. https://doi.org/10.5281/ZENODO.14752456.
[70] Polineni, T. N. S., & Ganti, V. K. A. T. (2019). Revolutionizing Patient Care and Digital Infrastructure: Integrating Cloud Computing and Advanced Data Engineering for Industry Innovation. World, 1, 1252.
[71] K. Patibandla and R. Daruvuri, "Reinforcement deep learning approach for multi-user task offloading in edge-cloud joint computing systems," International Journal of Research in Electronics and Computer Engineering, vol. 11, no. 3, pp. 47-58, 2023.
[72] Sikha, V. K. 2022. Mastering the Cloud - How Microsoft's Frameworks Shape Cloud Journeys. Zenodo. https://doi.org/10.5281/ZENODO.14660200.
[73] R. Daruvuri, "Dynamic load balancing in AI-enabled cloud infrastructures using reinforcement learning and algorithmic optimization," World Journal of Advanced Research and Reviews, vol. 20, no. 1, pp. 1327–1335, Oct. 2023, doi: 10.30574/wjarr.2023.20.1.2045.
[74] Sikha, V. K. 2023, June 30. The SRE Playbook: Multi-Cloud Observability, Security, and Automation. Journal of Artificial Intelligence & Cloud Computing. Scientific Research and Community Ltd.
[75] R. Daruvuri, "Harnessing vector databases: A comprehensive analysis of their role across industries," International Journal of Science and Research Archive, vol. 7, no. 2, pp. 703–705, Dec. 2022, doi: 10.30574/ijsra.2022.7.2.0334.
[76] Sikha, V. K. 2023. Cloud-Native Application Development for AI-Conducive Architectures. Zenodo. https://doi.org/10.5281/ZENODO.14662301.
[77] R. Daruvuri, "An improved AI framework for automating data analysis," World Journal of Advanced Research and Reviews, vol. 13, no. 1, pp. 863–866, Jan. 2022, doi: 10.30574/wjarr.2022.13.1.0749.

[78] Mandala, G., Reddy, R., Nishanth, A., Yasmeen, Z., & Maguluri, K. K. (2023). AI and ML in Healthcare: Redefining Diagnostics, Treatment, and Personalized Medicine. International Journal of Applied Engineering & Technology, 5(S6).
[79] Pandugula, C., & Yasmeen, Z. (2019). A Comprehensive Study of Proactive Cybersecurity Models in Cloud-Driven Retail Technology Architectures. Universal Journal of Computer Sciences and Communications, 1(1), 1253. Retrieved from https://www.scipublications.com/journal/index.php/ujcsc/article/view/1253
[80] Vankayalapati, R. K. (2022). AI Clusters and Elastic Capacity Management: Designing Systems for Diverse Computational Demands. Available at SSRN 5115889.
[81] Syed, S. (2019). Data-Driven Innovation in Finance: Crafting Intelligent Solutions for Customer-Centric Service Delivery and Competitive Advantage. Available at SSRN 5111787.