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CLOUD-POWERED MACHINE LEARNING FOR STREAMLINED INSURANCE CLAIMS PROCESSING ENHANCING EFFICIENCY AND CLIENT SATISFACTION

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ABSTRACT

In response to evolving customer needs, insurance organizations are modernizing their processes, particularly in the health sector and emphasize claims processing. By integrating various stakeholders such as clinics, physicians, and security networks via cloud technology, data flow is improved, facilitating faster case approval. Challenges like data breaches and lack of transparency are addressed through proposed cloud-based solutions for secure and transparent claims administration. However, ensuring the trustworthiness of system users remains a concern. The research focuses on developing a cloud-based system prioritizing simplicity and trustworthiness for secure and transparent health insurance claims processing. Key steps in automating insurance claim processing leveraging cloud-based technologies and machine learning are outlined, including self-service FNOL intake, Intelligent Document Processing (IDP), Smart Claim Triage with Predictive Analytics, and evaluation using ML. The proposed model Hybrid Convolutional Long Short Term Memory (HCLSTM) aim to enhance injury analysis within the insurance claim process, providing deeper insights and improving accuracy.

Keywords: Insurance Claims Processing; Cloud; Machine Learning; IDP; HCLSTM.

1. INTRODUCTION

In today's rapidly evolving healthcare landscape, the efficient processing of insurance claims stands as a cornerstone of effective patient care and financial stability for healthcare providers and insurers alike. However, the traditional manual processes involved in claims processing often lead to delays, errors, and inefficiencies, ultimately impacting both the quality of patient care and the satisfaction of policyholders [1]. Recognizing the pressing need for innovation in this critical area, the integration of automation technologies, coupled with a focus on enhancing user satisfaction, emerges as a pivotal strategy for revolutionizing insurance claim processing within the healthcare sector [2, 3]. Automating insurance claim processing holds immense promise for streamlining workflows, reducing administrative burden, and improving overall operational efficiency in healthcare organizations. By leveraging cutting-edge technologies such as Robotic Process Automation (RPA), Machine Learning (ML), and cloud computing, insurers can transform cumbersome manual tasks into automated, intelligent processes that deliver faster, more accurate outcomes [4]. This transformation not only accelerates claims processing but also enhances data accuracy, compliance, and fraud detection capabilities, thereby safeguarding the integrity of the entire insurance ecosystem [5]. At the heart of the drive towards automation lies a fundamental commitment to prioritizing user satisfaction, particularly from the perspective of patients and healthcare providers.

The traditional model of claims processing often entails cumbersome paperwork, lengthy processing times, and opaque communication channels, leading to frustration and dissatisfaction among policyholders and healthcare professionals alike. By embracing automation technologies, insurers can revolutionize this experience by offering seamless, user-friendly interfaces for claims submission, tracking, and resolution. Moreover, automation facilitates proactive communication and transparency throughout the claims lifecycle, empowering patients with real-time updates, personalized assistance, and greater control over their healthcare journey [6, 7]. Through self-service portals, mobile apps, and AI-powered chatbots, policyholders can easily initiate claims, submit relevant documentation, and receive instant feedback, significantly enhancing their overall experience and reducing the burden on customer support teams [8]. Furthermore, automation enables healthcare providers to focus more on delivering quality care rather than grappling with administrative tasks associated with claims processing [9].

By seamlessly integrating claims data with electronic health records (EHR) systems and practice management software, providers can streamline workflows, optimize revenue cycles, and allocate resources more effectively, ultimately leading to improved patient outcomes and satisfaction [10, 11]. In digital transformation, the pursuit of automation in insurance claim processing represents not only a strategic imperative but also a moral obligation to prioritize user satisfaction and deliver superior healthcare experiences [12]. Through a synergistic combination of advanced technologies and a user-centric approach, healthcare insurers can unlock unprecedented efficiency gains, cost savings, and competitive advantages while fostering trust, loyalty, and satisfaction among policyholders and healthcare stakeholders [13]. This paper explores the multifaceted benefits of automating insurance claim processing within the healthcare sector, with a focus on enhancing user satisfaction as a cornerstone of transformative change.

The contributions of this paper are manifested below,

- The research introduces a novel cloud-based system designed specifically for the secure and transparent processing of health insurance claims. This contributes to enhancing trust and reliability in the insurance process.
- By prioritizing simplicity and trustworthiness in the design of the system, the research ensures that both insurers and policyholders can easily navigate and rely on the platform, thereby improving user experience and satisfaction.
- Through the use of machine learning models, particularly artificial neural networks (ANN) and Naive Bayes, the system accurately assesses injuries and damages depicted in medical images and reports related to insurance claim, enhancing the precision of claim evaluations.
- The research proposes advanced models like HCLSTM, aimed at further enhancing injury analysis, providing deeper insights into injury characteristics, and ultimately improving accuracy in healthcare insurance claims processing.

This paper is structured as follows for the remainder of it. There is a list of related works in Part II. In Section III, the proposed protocol is presented and explained. The results and discussion are then presented in part IV, and the conclusion is presented in section V.

2. LITERATURE REVIEW

Using Porter's value chain and Berliner's insurability criteria, Eling and Lehmann [14] investigated the effects of digital revolution on the insurance industry in 2018. Our findings highlight four key challenges: enhancing customer experience, optimizing business processes, innovating new products, and adapting to cross-industry competition. Additionally, we identify three critical areas of change concerning insurability: information asymmetry, technological advancements, and interconnected systems.

In 2022, Amponsah et al. [15] developed a blockchain-based solution to safeguard its financial integrity. The paper outlines system design, including smart notification and claim processing, evaluated using the DeLone & McLean Information Systems Success Model, highlighting the influence of information quality and user satisfaction.

In 2021, Hassan et al. [16] focused on predicting medical insurance costs using ML techniques. Employing a range of algorithms including Linear Regression, Support Vector Regression, and Random Forest, the research utilizes a medical insurance dataset from KAGGLE to demonstrate predictive accuracy and model comparison.

In 2020, Mubarakali [17] used a secure and Robust Healthcare-based Blockchain (SRHB) approach, employing Attribute-based Encryption for secure data transmission. Wearable devices collect patient data, which is stored in a cloud server. Doctors and insurance agents review this data for medical treatment and insurance purposes, ensuring privacy through blockchain implementation.

In 2021, Kohli et al. [18] examined a three-level cloud-based application called "e-Health Cloud" and proposes an enhanced model to revamp the outdated healthcare framework. The model integrates various stakeholders to enhance healthcare management, leveraging Google Cloud Healthcare API with HL7.FHIR and

DICOM support. Additionally, it addresses security concerns and includes GPS tracking for patient location monitoring.

In 2022, Kaushik et al. [19] used and assesses a regression-based AI model for predicting health insurance premiums. Utilizing parameters like age, gender, BMI, children count, smoking habits, and location, an artificial neural network predicts individual insurance costs accurately.

3. PROPOSED METHODOLOGY

Automating insurance claim processing holds immense potential for revolutionizing the healthcare sector by improving both operational efficiency and patient satisfaction. This paper explores the transformative impact of leveraging cloud-based technologies, Machine Learning (ML), to streamline and optimize the claims processing workflow within healthcare insurance. Figure 1 depicts the flow chart for health insurance claim processing.

3.1. Self-Service FNOL Intake

The implementation of digital First Notice of Loss (FNOL) intake systems empowers patients to seamlessly submit insurance claims through user-friendly interfaces such as web-based forms. This minimizes manual data entry efforts and expedites the claims reporting process, enhancing overall patient experience.

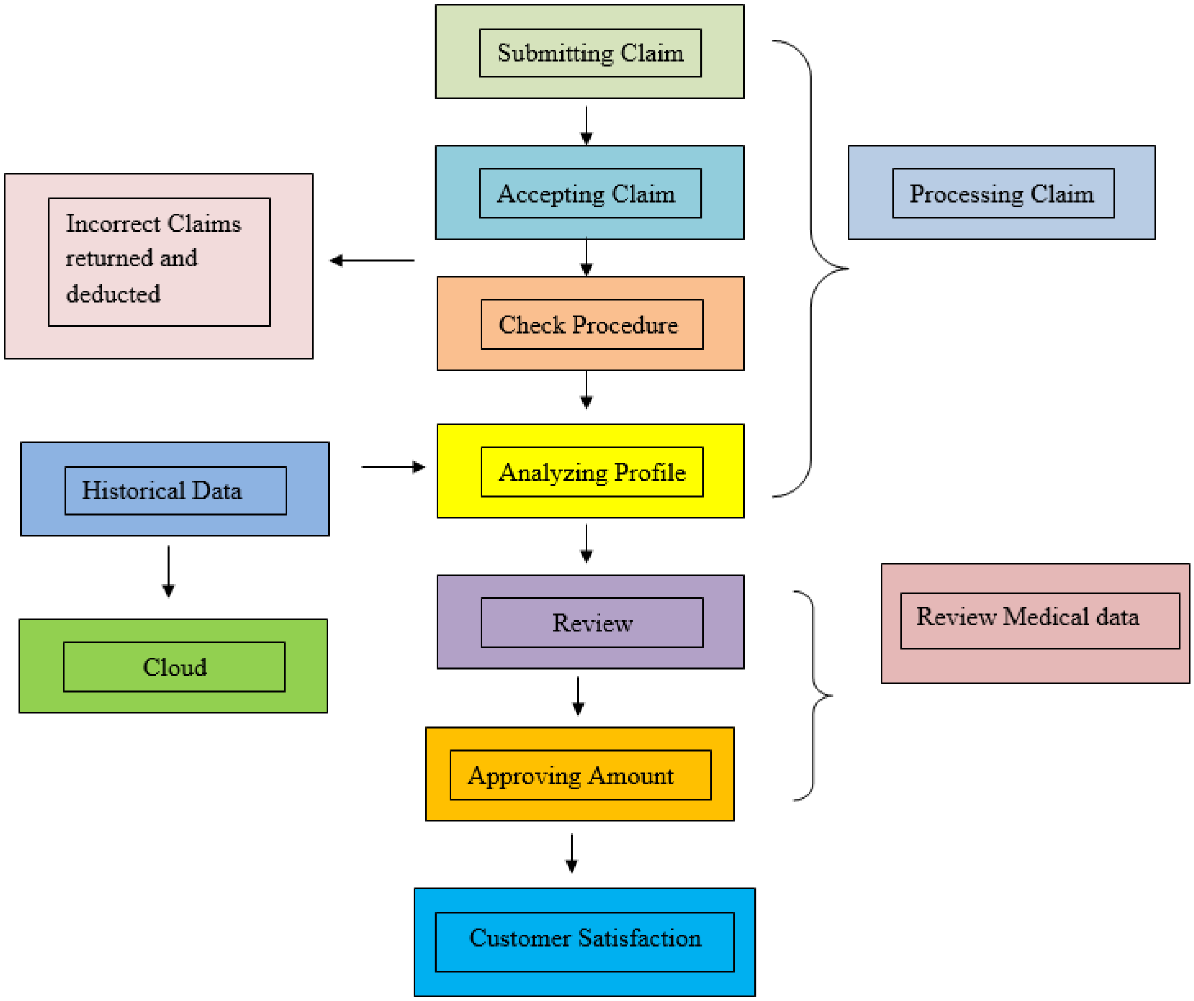

Figure 1: Flow chart of health insurance claim processing

Web-based forms are digital forms that users can access and fill out through a web browser on their computer or mobile device. These forms are typically hosted on a website or web application. Users navigate to the insurance company's website or online portal where they find a section dedicated to submitting insurance claims. They then fill out the required fields in the form, providing information such as their personal details, policy number, details of the incident or claim, and any supporting documentation. Web-based forms are designed to be intuitive and user-friendly, with clear instructions and easy-to-navigate fields. They often include validation checks to ensure that users enter accurate information and prevent errors. Additionally, they may offer features such as auto-fill for repetitive information and progress indicators to show users how far along they are in the form. Web-based forms offer convenience and accessibility, allowing users to submit claims at any time from any location with an internet connection. They simplify claims submission, cutting manual entry and paperwork for all.

3.2. Intelligent Document Processing (IDP)

IDP technology enhances the accuracy and efficiency of document processing within healthcare insurance. Insurance companies can extract structured data from unstructured documents using sophisticated techniques like natural language processing (NLP), which expedites the processing of claims and lowers administrative burden.

3.2.1. NLP

The study of how computers and human language interact is known as natural language processing, or NLP. It makes it possible for computers to meaningfully and practically comprehend, interpret, and produce human language. NLP approaches are used in document processing to examine text documents and extract pertinent information.

- **Tokenization**

The process of dividing text into smaller pieces known as tokens is known as tokenization. Words, phrases, or even symbols could be used as these tokens. It facilitates the division of text into meaningful parts, which makes it simpler for computers to continue processing and analyzing the content. Tokenizing a statement into individual words or phrases, for instance, enables more accurate analysis.

- **PartofSpeech (POS) Tagging**

Assigning grammatical categories or tags to every word in a sentence is known as POS tagging. It aids in comprehending the text's syntactic structure and determining each word's function inside a phrase. To analyze the text's meaning and context, this information is essential.

- **Named-Entity-Recognition (NER)**

NER is the process of locating and classifying named entities in text documents, including individuals, groups, places, dates, and numerical expressions. It assists in the selective extraction of information from unstructured text, which is beneficial for applications like knowledge extraction and information retrieval.

NLP algorithms process textual data to identify patterns, relationships, and entities within documents. By analyzing the content of documents, insurers can extract structured data such as policy numbers, claim details, patient demographics, and medical procedures mentioned in the text. This structured data can then be used for various purposes such as claims processing, fraud detection, and data analysis.

3.3. Smart Claim Triage with Predictive Analytics

Smart Claim Triage with Predictive Analytics is a process used by healthcare insurers to prioritize and allocate resources effectively for processing insurance claims. By using historical data and predictive analytics techniques, insurers can identify high-priority claims that require immediate attention, thereby improving the efficiency of claims processing and enhancing patient outcomes.

3.3.1. Risk Assessment Models

In healthcare insurance, risk assessment models can include a range of elements and methods to analyze the risk attached to each claim. A claim's risk can be affected by variables like geography, occupation, age, and gender. A claim's possible risk can be evaluated by looking at the patient's medical history, including any pre-existing conditions, prior treatments, and family medical history. Chronic illnesses or previous medical procedures may increase the cha of future claims. Different types of claims may pose varying levels of risk. For instance, claims related to chronic diseases or complex medical procedures may require more resources and entail higher costs compared to routine check-ups or preventive care. The complexity of the medical treatment or procedure involved in the claim can influence the risk assessment. More complex procedures may carry higher risks of complications or adverse outcomes, leading to increased costs for insurers. Analyzing the patient's previous claims history, including the frequency, severity, and patterns of past claims, can help assess the likelihood of future claims. Patients with a history of frequent or high-cost claims may be considered higher risk. The reputation and track record of healthcare providers involved in the claim, such as hospitals, clinics, or individual practitioners, can impact the risk assessment. Providers with a history of quality care and positive outcomes may lower the overall risk associated with the claim. Localized factors such as regional health trends, prevalence of diseases, availability of healthcare facilities, and socio-economic conditions can influence the risk assessment. Insurers may adjust risk assessments based on geographic variations in healthcare utilization and outcomes. External data sources, such as public health databases, environmental factors, socio-economic indicators, and population health metrics, can provide additional insights into the risk profile of patients and claims.

3.4. Enhancing Healthcare Insurance with Telematics and Cloud

Telematics and Internet of Things (IoT) integration in healthcare insurance revolutionizes the way patient data is collected, analyzed, and utilized for claims assessment. The real-time data collected by IoT sensors is often stored and processed in cloud-based platforms or servers. Cloud technology provides scalable and flexible storage solutions, allowing healthcare insurers to efficiently manage large volumes of data generated by IoT devices. Cloud platforms enable remote access to IoT-generated data from any location with an internet connection. Healthcare insurers, healthcare providers, and other stakeholders can securely access and collaborate on patient data, claims information, and analytics reports stored in the cloud. Robust security mechanisms, including encryption, access limitations, and frequent security audits, are put in place by cloud service providers to safeguard private medical records kept on the cloud. Cloud-based healthcare solutions are made to comply with industry standards for data privacy and security as well as regulatory needs through compliance frameworks like the US's HIPAA (Health Insurance Portability and Accountability Act). Healthcare insurers can reduce the risk of data breaches or unauthorized access, improve data security, and comply with regulatory requirements by utilizing cloud-based infrastructure.

3.5. Evaluation Using ML

Evaluation using ML technology automates the process of analyzing medical images and reports to identify and quantify injuries or damages within the insurance claim process. By leveraging machine learning techniques, insurers can accurately assess various types of injuries and damages, enhancing the efficiency and accuracy of claims processing in healthcare insurance. ML models can continuously learn and adapt to new data, improving their performance over time and enabling more robust and efficient damage evaluation. The existing models like ANN and Naive Bayes are utilized to analyze labeled medical image datasets, learning injury patterns. The proposed models HCLSTM aim to enhance the analysis of insurance claims, offering deeper insights into injury characteristics and improving accuracy in healthcare.

3.5.1. ANN

- Input-Layer

The input layer simply passes raw data or features to the hidden layers for processing, assigning one neuron per feature. No computational operations take place within this layer.

- Hidden-Layers

Hidden layers perform the core computation in neural networks. Neurons in a hidden layer receive inputs from the previous layer, calculate a weighted sum, and then apply an activation function to produce an output as described in Eq. (1). The arrangement of hidden layers is customized based on the complexity of the problem.

$$a_{ij} = f\left(\sum_{k=1}^{n_{i-1}} w_{ik} a_{ik} + b_{ij}\right) \quad (1)$$

In a hidden layer, the output of each neuron is calculated as the weighted sum of its inputs plus a bias factor.

- Output-Layer

The output layer produces the final output of the neural network, with the quantity of neurons determined by the nature of the problem.

3.5.2. NaiveBayes

It is a family of probabilistic classifiers based on Bayes Theorem, with the "naive" assumption of feature independence. Despite its simplicity, Naive Bayes classifiers are widely used in various applications due to their efficiency and effectiveness. It assumes that the features used to describe an observation are conditionally independent given the class label. This simplifies the computation and makes the algorithm tractable even with high-dimensional data. The central idea of Naive Bayes is the Bayes' Theorem, which determines the chance of a hypothesis in light of available data. Eq. (2) is used to express it.

$$P(E|F) = \frac{P(F|E) \times P(E)}{P(F)} \tag{2}$$

Where, $P(F|E)$ is the posterior probability of E given F, $P(F|E)$ is the chance of F given E, $P(E)$ and $P(F)$ are the prior probabilities of E and F, respectively.

3.5.3. HCLSTM

CNN, a type of deep learning model, are adept at learning and extracting significant patterns from raw data like images. They comprise Convolutional, pooling, activation, fully connected layers, and an output layer. Convolutional layers extract features using filters, while pooling layers downsample features. Activation functions introduce non-linearities, and fully connected layers make predictions. During training, CNN learn to optimize their parameters through techniques like backpropagation and gradient descent, minimizing a chosen loss function. This iterative process allows CNN to adapt and improve their ability to recognize and classify objects in images. The HCLSTM architecture is depicted in Figure 2.

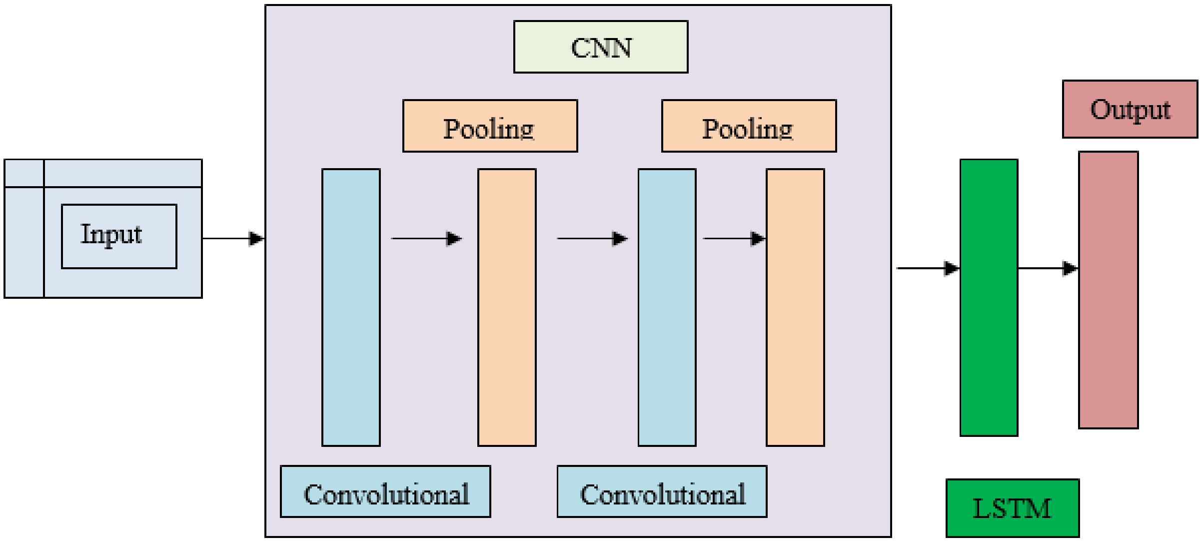

Figure 2: HCLSTM Architecture

Recurrent neural networks (RNN) of the Long Short-Term Memory (LSTM) type were created to solve the problem of identifying long-term dependencies in sequential input. Because of their memory blocks, which allow them to retain information over extended periods of time, they are particularly well-suited for tasks involving time-series data and natural language processing.

- Input Layer: Receives sequential data input.
- Hidden Layer: Contains LSTM units responsible for processing and retaining information.
- Output Layer: Produces the final output based on the processed information.

LSTM replaces the basic units of regular RNNs with memory cells, which allow them to retain information over long sequences. LSTM units have three main gates: input gate, forget gate, and output gate.

- Input Gate: Regulates how fresh data enters the memory cell.
- Forget Gate: Selects the data from the memory cell to remove.
- Output Gate: Adjusts the output according to the input's previous state and present value.

The activation of each LSTM unit at time l_t is calculated using Eq. (3):

$$l_t = \sigma(wm_{i,l} \cdot x_t + wm_{h,l} \cdot l_{t-1} + bi) \quad (3)$$

Where, l_t and l_{t-1} represent the activation at time respectively, σ is a non-linear activation function, $wm_{i,l}$ is the input-hidden weight matrix, $wm_{h,l}$ is the hidden-hidden weight matrix, bi is the hidden bias vector, and x_t is the input at time t. LSTM networks excel at capturing long-term dependencies in sequential data. They mitigate the problem of gradient vanishing, allowing for more effective learning over longer sequences.

An correct and timely assessment of injuries guarantees quick medical attention, which makes treatments easier to receive. This proactive strategy highlights the importance of effective damage appraisal methods and improves patient outcomes while also increasing satisfaction levels within healthcare insurance claims.

4. RESULT AND DISCUSSION

4.1. Experimental Setup

The proposed model HCLSTM is implemented and compared with existing model ANN, and Naive Bayes.

4.2. Dataset Description

The Sample Insurance Claim Prediction Dataset [20] provides essential information for predicting insurance claims. Age, body mass index (BMI), smoking status, gender, residence area, number of children, and personal medical expenses are among the characteristics that are included. This well-documented dataset is suitable for various learning, research, and application purposes in the insurance domain. With its clean and well-maintained data, it offers high-quality insights into insurance claim prediction. Additionally, it comes with a range of high-quality notebooks, further enhancing its usability for analysis and modeling. Overall, this dataset serves as a valuable resource for exploring and developing predictive models to optimize insurance claim processing and decision-making.

4.3. Overall Performance Analysis of Existing and Proposed Model

Table 1: Comparison of Proposed and Existing Model

Methods	Accuracy	Precision	F1 Score	Specificity
Proposed HCLSTM	98.31	97.23	98.51	90.01
ANN [21]	96.21	95.31	97.48	90.89
Naive Bayes [21]	95.34	94.16	96.24	89.21

Table 1 presents a comparison of performance metrics among different models used for analyzing labeled medical image datasets to learn injury patterns. Three models are evaluated: the proposed HCLSTM (Hierarchical Convolutional Long Short-Term Memory), Existing models ANN (Artificial Neural Network), and Naive Bayes. The proposed HCLSTM model achieves the highest accuracy of 98.31%, indicating its superior ability to correctly classify injury patterns compared to ANN and Naive Bayes. Similarly, HCLSTM also demonstrates higher precision (97.23%) and F1 score (98.51%), reflecting its capability to minimize false positives and negatives while maintaining a balance between precision and recall. Moreover, the model exhibits a specificity of 90.01%, indicating its proficiency in correctly identifying negative cases. In contrast, although ANN achieves respectable accuracy (96.21%), precision (95.31%), and F1 score (97.48%), it falls slightly short compared to HCLSTM in terms of overall performance. Naive Bayes, while also effective, shows slightly lower accuracy (95.34%), precision (94.16%), and F1 score (96.24%) compared to both HCLSTM and ANN. Additionally, Naive Bayes has the lowest specificity (89.21%), indicating a higher rate of false negatives. The results suggest that the proposed HCLSTM model outperforms existing methods, including ANN and Naive Bayes.

4.4. Graphical Representation of Existing and Proposed Model

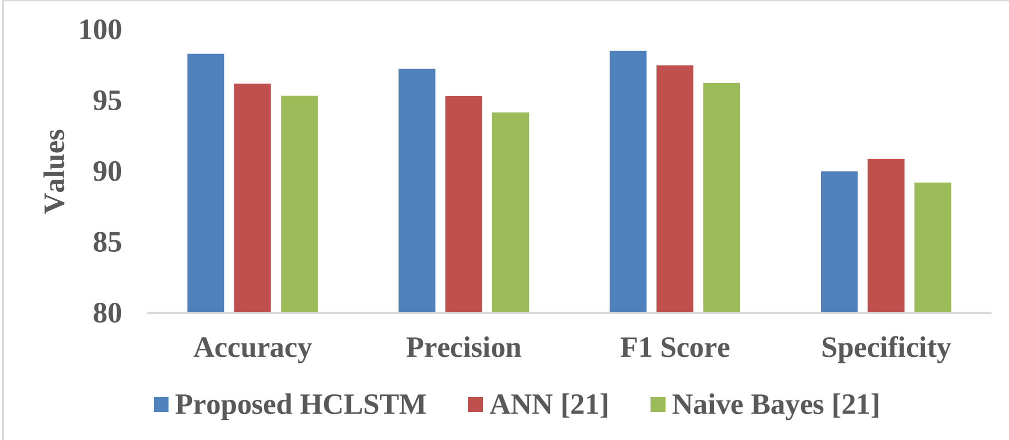

Figure 3: Comparison of existing and proposed models graphically

Figure 3 visually compares the performance of existing and proposed models. It illustrates the differences in accuracy, precision, F1 score, and specificity, highlighting the superior performance of the proposed model, HCLSTM, in accurately analyzing insurance claim data compared to existing models like ANN and Naive Bayes.

5. CONCLUSION

This paper developed on a cloud-based system for secure and transparent health insurance claims, prioritizing simplicity and trustworthiness. Automating insurance claim processing in healthcare involved several key steps leveraging cloud-based technologies and ML. First, FNOL intake systems allowed patients to easily submit claims, reducing manual entry and expediting the process. IDP used NLP to extract data from documents, speeding up claims handling. Smart Claim Triage with Predictive Analytics prioritized claims based on historical data, improving resource allocation. Evaluation using ML analyzed medical images and reports, accurately assessing injuries and damages related to insurance claims. The existing models like ANN and Naive Bayes were utilized to analyze labeled medical image datasets, learning injury patterns. Proposed models like HCLSTM aimed to enhance injury analysis, offering deeper insights and improving accuracy. The proposed model was achieved high accuracy of 98.31%.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Not Applicable

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