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LEVERAGING CLOUD PLATFORMS FOR AI-DRIVEN UNDERWRITING IN INSURANCE

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ABSTRACT

Cloud platform integration with AI-driven underwriting processes is revolutionizing the insurance sector by improving decision-making and risk assessment accuracy and efficiency. The application of cloud-based technologies in the underwriting process was examined in this research, with a particular emphasis on data collection, pre-processing, feature extraction, model selection, evaluation, validation, ongoing monitoring, and data storage. Thorough data collection guarantees that the information is relevant and complete, and preparation procedures deal with problems like inconsistent data, outliers, and missing numbers. Utilizing cloud capabilities for efficiency and scalability, feature extraction techniques such as Linear Discriminant Analysis (LDA) as well as normalization and standardization optimize data for analysis. Model selection Convolutional Recurrent Artificial Long Short-Term Memory Networks (CRAL) improves underwriting accuracy by processing sequential data and extracting complex patterns. CRAL incorporates advanced AI models such as Convolutional Recurrent Neural Networks (CRNN), Artificial Neural Networks (ANN), and Long Short-Term Memory Networks (LSTM). Over time, the resilience and dependability of the model are ensured via evaluation, validation, and ongoing monitoring. Data scalability, accessibility, and compliance with data governance rules are all made easier by securely storing data on the cloud. Insurance companies may improve the quality of underwriting judgments, minimize risks, and expedite processes by utilizing cloud platforms for AI-driven underwriting.

Keywords: *Underwriting; Insurance; LDA; CRAL; ANN; CRNN; LSTM.*

1. INTRODUCTION

In the insurance business, underwriting is a crucial step that establishes premium price and risk acceptability. It is necessary for insurance companies to remain financially stable and viable over the long run. Underwriting has historically placed a strong emphasis on the manual evaluation of experienced underwriters, a process that is labor-intensive and prone to human error [1, 2]. But the underwriting industry is changing dramatically as a result of artificial intelligence (AI) and machine learning techniques [3]. Automation and optimization are becoming more and more prevalent. AI-driven underwriting is an innovative method that uses data analytics and algorithms to improve and expedite the underwriting process [4]. AI may give insurers faster decision-making times, more precise risk assessments, and ultimately, increased operational efficiency by utilizing massive data sets and advanced modeling approaches. For insurers, the use of AI in underwriting opens up a world of possibilities and benefits [5, 6].

First off, AI systems can analyze large, complicated datasets at a speed and accuracy never seen before, which makes it possible to assess risk variables more thoroughly [7]. As a result, insurers are able to determine applicants' suitability for insurance and set rates with greater knowledge, which improves risk management procedures and creates more specialized insurance products [8]. Moreover, by streamlining the application process and lowering the requirement for copious documentation, AI-powered underwriting systems may improve the entire client experience. Insurance companies may provide policyholders with a more seamless and responsive service, which will increase customer happiness and loyalty, by utilizing AI algorithms that can automate repetitive operations and provide real-time insights [9]. Furthermore, AI-driven underwriting has the potential to lessen decision-making bias and increase underwriting consistency. AI algorithms function according to predetermined norms and objective criteria, as opposed to human underwriters who could be swayed by subjective variables. This ensures a more uniform and equitable assessment procedure for all applicants [10]. In addition to encouraging accountability and openness, this also lessens the possibility of discriminatory practices. AI-powered underwriting not only improves operational effectiveness and offers advantages for risk management, but it also creates new opportunities for product development and innovation in the insurance sector [11].

Insurers can proactively modify their underwriting methods and offers to satisfy changing demands by utilizing advanced analytics and predictive modeling to obtain deeper insights into customer behavior, market trends, and emerging hazards [12]. All things considered, AI-driven underwriting is a revolutionary paradigm change in the insurance sector that promises to upend established underwriting procedures and open up new avenues of efficiency, accuracy, and value for both policyholders and insurers. The future of underwriting has enormous promise for innovation, growth, and sustainability in the ever-changing insurance industry as long as insurers continue to adopt AI technologies. The contributions to this work are listed as follows:

- This paper contributes by presenting optimized data processing techniques, including data collection, pre-processing, and feature extraction, tailored specifically for underwriting tasks. Techniques such as Linear Discriminant Analysis (LDA), normalization, and standardization are highlighted, demonstrating their effectiveness in enhancing data quality and facilitating accurate risk assessment.
- This paper contributes by emphasizing the selection of advanced AI models such as CRNN, ANN, and LSTM for underwriting tasks. These models offer superior capabilities in processing sequential data, extracting complex patterns, and making informed decisions based on historical information, thereby improving underwriting accuracy and efficiency.
- It contributes by highlighting the importance of secure data storage in the cloud and implementing compliance measures to protect sensitive information. By storing underwriting data securely and ensuring compliance with data governance regulations, insurers can safeguard customer privacy, mitigate risks, and maintain legal compliance in the underwriting process.

The rest of this paper is organized as follows. The section II provides related works, and the proposed methodology is explained in the section III. The result and discussion is then presented in the section IV, followed by the conclusion in the section V.

2. LITERATURE REVIEW

Automated chatbots can improve consumer value creation, according to research done in 2018 by Riikkinen *et al.* [13]. Within a conceptual framework, it incorporates reverse customer data use, artificial intelligence, and service logic. Four metaphors that describe how insurance chatbots assist value generation are identified through illustrated case studies. Though conceptual in nature, the framework highlights the novelty of chatbots and provides insurance businesses with insights to connect their services with consumer value generation processes.

Predictive analytics was employed in 2018 by Boodhun and Jayabalan [14] to automate the underwriting process and increase productivity. Dimensionality reduction methods such as PCA and CFS were applied to real-world data. The use of REPTree classifiers and multiple linear regression as machine learning methods was made. The results show that Multiple Linear Regression worked well under PCA, while REPTree performed best under CFS, obtaining the lowest MAE and RMSE values. The insurance industry's underwriting process is depicted in Figure 1.

Figure 1: Underwriting Process [18]

Underwriting difficulties are addressed in 2018 by Dubey *et al.* [15] who discuss the shift from antiquated systems to automated data collecting. Underwriters have historically examined client data manually, which has resulted in inefficiencies. Automated analysis of unstructured emails is facilitated by integrating artificial intelligence, notably Natural Language Processing. Important features are extracted from these emails by statistical machine learning classifiers in order to identify appropriate insurance policies and recommendations. The main objective of the project is to increase productivity and automate underwriting procedures in order to properly manage dynamic conditions.

Toshmurzaevich [16] examined underwriting economic aspects, different methods, and importance in life insurance in 2020. It talks about how digitizing underwriting is essential to the growth of the industry. Regardless of the kind of insurance product, the article highlights a gradual, multidimensional approach to underwriting during the conclusion of life insurance contracts in order to achieve the best possible risk management and operational efficiency.

Machine learning algorithms were employed by Yang [17] in 2021 as a substitute for the laborious, conventional insurance underwriting procedures. Effective risk assessments can be obtained by utilizing technological innovations, especially those related to AI and ML. The Prudential Insurance dataset is used to evaluate different feature engineering approaches. The findings reveal that gradient boosting performs better and is more robust for insurance underwriting tasks than kth nearest neighbor, multinomial logistic regression, and random forest.

3. PROPOSED METHODOLOGY

Underwriting an insurance policy is evaluating the risks of prospective policyholders in order to establish the terms of coverage. Difficulties include missing data, incomplete risk assessment, and regulatory compliance. This work reduces these by using cutting-edge AI models (ANN, LSTM, and CNN) for accurate risk assessment.

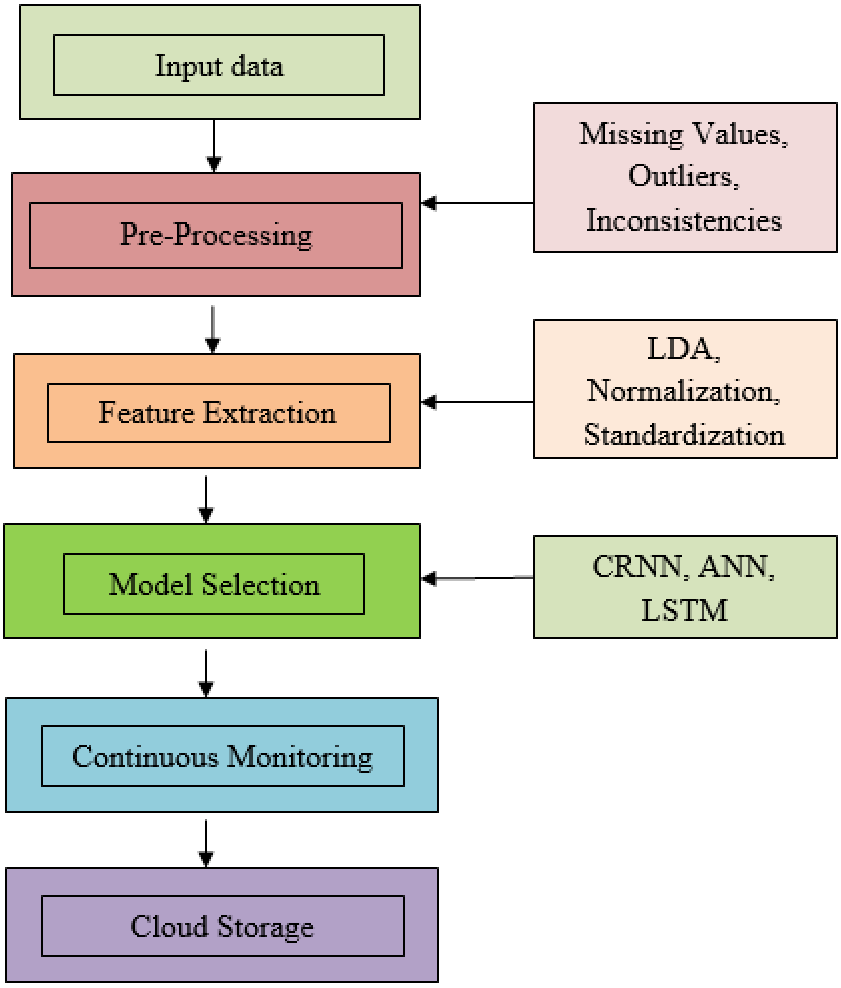

Figure 1: Overall Proposed Architecture

It also places a strong emphasis on compliance procedures and safe cloud storage to protect private data. By lowering the possibility of data breaches and guaranteeing regulatory compliance, these measures improve the efficiency and dependability of the underwriting process. Figure 2 shows the overall suggested architecture.

3.1. Data Collection and Pre-Processing

Pre-processing and data collecting are essential phases in the underwriting process that provide the groundwork for precise risk evaluation and insurance decision-making. First and foremost, collecting complete data entails locating pertinent data regarding the policy type, the applicant, and other relevant variables. Personal information, medical history, financial records, and any other pertinent data points may be included in this. To get a comprehensive understanding of the risk involved, it is imperative to ensure that the data is relevant and full. Pre-processing procedures are carried out on the data after it is gathered to get it ready for analysis. In order to fix any problems like missing numbers, outliers, and inconsistencies, the data must be cleaned. To maintain data integrity, missing values are imputed or eliminated, outliers are found and either fixed or marked for additional research, or discrepancies are fixed. Additionally, data standardization and normalization can be used to guarantee format and scale uniformity among various variables. This makes it easier to compare and analyze data more accurately while underwriting. Pre-processing and data gathering are crucial phases of the underwriting process because they guarantee the consistency, accuracy, and dependability of the data used to estimate risk. In the end, insurers may improve the overall quality of their underwriting process, make better decisions, and efficiently minimize risks by obtaining thorough and clean data.

3.2. Feature Extraction

In order to properly create predictive models, this phase sought to discover and choose the most pertinent variables or qualities from the obtained data. This step entails using a variety of approaches, including transformation, feature engineering, and dimensionality reduction, to extract meaningful features from the data that represent significant patterns and correlations. Techniques for dimensionality reduction are employed to lower a dataset's feature count while maintaining its critical information.

3.2.1. LDA

One commonly used method is LDA, utilized in statistics, pattern recognition, and machine learning, determines a linear combination of features to express one dependent variable. Unlike PCA and factor analysis, LDA explicitly models differences between data classes, rather than ignoring or focusing solely on similarities. LDA identifies vectors in the data space that best discriminate between classes, creating a linear combination of independent features to maximize mean differences between classes as per Eq. (1) and Eq. (2).

$$sw = \sum_{j=1}^{c} \sum_{i=1}^{nj} \left(x_i^j - \mu_j\right)\left(x_i^j - \mu_j\right)^B \tag{1}$$

x_i^j denotes the ith sample of class, μ_j is the mean of class j, c represents the number of classes, nj signifies the number of samples in class j, μ denotes the mean of all classes.

$$sw = \sum_{j=1}^{c} \left(\mu_j - \mu\right)\left(\mu_j - \mu\right)^T \tag{2}$$

Integrating cloud capabilities into the dimensionality reduction step enhances scalability, efficiency, and flexibility in managing large-scale data processing tasks. By leveraging cloud infrastructure and services, organizations can accelerate dimensionality reduction computations and optimize algorithm performance, ultimately improving the quality of downstream analytics and decision-making processes.

3.2.2. Normalization and Standardization

Standardization and normalization are crucial preprocessing methods in data analysis because they guarantee that characteristics are scaled uniformly. Standardization converts features to have a mean of 0 and a standard deviation of 1, whereas normalization scales features to a standard range, usually between 0 and 1. By supporting an equal contribution from all features during analysis, these strategies lessen the dominance of features with bigger scales. Normalization and standardization improve the performance and interpretability of machine learning models in underwriting by normalizing the scale and distribution of information. This makes risk assessment and decision-making more precise. Both methods, which are represented by Eq. (3) and Eq. (4), are crucial for ensuring that the magnitude and distribution of features in data are constant.

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

$$x_{stan} = \frac{x - \mu}{\sigma} \tag{4}$$

Where, x is the original feature value, x_{min} and x_{max} are the minimum and maximum values of the feature, μ is the mean of the feature, and σ is the standard deviation of the feature.

3.3. Model Selection

Convolutional Recurrent Neural Networks (CRNN), Artificial Neural Networks (ANN), and Long Short-Term Memory Networks (LSTM) are examples of AI models that CRAL integrates to improve underwriting accuracy and efficiency. These models make use of their abilities to process sequential data, extract intricate patterns, and make decisions based on past data.

3.3.1. CRNN

CNNs are a subset of deep learning models that are skilled in identifying and deriving meaningful patterns from unprocessed input, such as photographs. Convolutional, pooling, activation, completely connected, and an output layer are among them. While pooling layers downsample features, convolutional layers use filters to extract features. Fully connected layers produce predictions, and activation functions incorporate non-linearities. CNNs are trained to minimize a selected loss function by optimizing their parameters using methods like gradient descent and backpropagation. CNNs are able to adjust and enhance their recognition and classification skills of objects in images through this iterative process. Three different sorts of layers commonly make up an ANN's architecture: input, hidden, and output layers. There are neurons, or nodes, in every layer, and information is carried by the connections between these neurons. A neural network built for sequential data is called an RNN. RNNs, in contrast to feedforward neural networks, have connections that form directed cycles, which allows them to handle sequential input and store hidden state information. Because the order of the input pieces matters, they are especially useful for jobs involving time series data or natural language processing. Recurrent units, such Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), are used by RNNs to update hidden states over time and manage long-term dependencies. They use methods such as Backpropagation through Time (BPTT) to update parameters according to the data's sequential structure. Furthermore, RNNs are used in security frameworks to continually monitor incoming data and identify anomalies or departures from predicted patterns that could point to system faults or security risks. The hidden state hs_t at time t in an RNN is computed using Eq. (5).

$$hs_t = \sigma(w_{hsi} i_t + w_{hshs} hs_{t-1} + bi_{hs}) \tag{5}$$

i_t represents the input at time, w_{hsi} is the weight matrix for the input, w_{hshs} is the weight matrix for the hidden state, bi_{hs} is the bias term, and σ denotes the activation function, typically a non-linear function such as the sigmoid or hyperbolic tangent $(tanh)$. The output $o_t$at time t is computed based on the hidden state and expressed as per Eq. (6).

$$o_t = softmax(w_{ohs} hs_t + bi_o) \tag{6}$$

Where, w_{ohs} is the weight matrix connecting the hidden state to the output, bi_o is the bias term, $softmax$ is the activation function, commonly used for multi-class classification problems. The RNN processes sequences by iterating through time steps, updating the hidden state at each step based on the current input and the previous hidden state.

3.3.2. ANN

- InputLayer

The input layer forwards raw data or features to hidden layers for processing, with one neuron per feature. No computation occurs within this layer.

- HiddenLayers

Hidden layers carry out the primary computation in neural networks. Neurons within a hidden layer receive inputs from the preceding layer, compute a weighted sum, and apply an activation function to generate an output. The configuration of hidden layers is tailored to problem complexity and calculated as per Eq. (7).

$$a_{ij} = f\left(\sum_{k=1}^{n_{i-1}} w_{ik} a_{ik} + b_{ij}\right) \quad (7)$$

The output of each neuron in a hidden layer is calculated using a weighted sum of inputs and a bias term.

- Output Layer

The output layer generates the neural network's final output, with the number of neurons determined by the problem type.

3.3.3. LSTM

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. (8):

$$l_t = \sigma(wm_{i,l} \cdot x_t + wm_{h,l} \cdot l_{t-1} + bi) \tag{8}$$

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.

3.4. Model Evaluation and Validation

To guarantee AI models' resilience and dependability in underwriting, it is essential to assess and validate them. This procedure entails evaluating the model's performance in terms of accuracy, consistency, and generalization capacity by applying relevant metrics and approaches. Cross-validation is one popular technique that divides the dataset into numerous folds or subsets. The model is then trained and evaluated several times using various combinations of these folds. By doing this, you can evaluate the model's performance on various data samples and make sure it has good generalization to new data. Another method is holdout validation, which involves separating the training data from a piece of the dataset that is designated as a validation set. To estimate the model's performance on unseen data, it is first trained on the training set and then assessed on the validation set. Furthermore, a number of metrics, including F1-score, recall, accuracy, and precision, can be used to objectively assess the model's performance. These measures shed light on several aspects of the predictive power of the model, including its accuracy in classifying positive and negative instances, its capacity to reduce false positives, and its capacity to increase genuine positives. Through the integration of evaluation and validation methodologies into the underwriting process, insurers can guarantee the dependability, precision, and ability of the AI models they utilize to make well-informed selections grounded in the available data. This lowers risks and raises trust in the underwriting choices the AI models make.

3.5. Continuous Monitoring

Ensuring the continuous functionality and dependability of AI-driven underwriting models in real-world settings requires the implementation of monitoring systems. With the use of these tools, insurers may monitor the performance of their models in real time, identify any irregularities or deviations, and take preventative action when necessary. Creating extensive dashboards that offer real-time insights into important performance indicators like accuracy, precision, recall, and F1-score is one method of keeping an eye on the performance of the model. With the use of these dashboards, insurers can see how the model behaves over time and spot any abrupt changes or patterns that can point to model problems. Establishing alerting systems that notify pertinent stakeholders when predetermined thresholds or criteria are surpassed is crucial, in addition to monitoring performance metrics. This makes it possible for prompt action to look into and resolve any problems before they get worse.

Insurers should also set up procedures for upgrading and retraining models in light of fresh data and changing underwriting specifications. This could entail setting up regular retraining cycles when the model is updated with new data to make sure it stays current and correct. Insurers also need to have procedures in place for dealing with model drift, which is the result of underlying data distribution shifting over time. Insurance companies can spot cases of model drift and implement suitable remedial measures, such retraining the model on more recent data, by closely observing model performance and comparing it to baseline metrics. Insurers can uphold excellent performance standards and flexibility in their underwriting procedures by remaining proactive.

3.6. Storing data in the cloud

Ensuring the availability, integrity, and confidentiality of sensitive data requires underwriting data to be stored securely on the cloud. Insurance companies can save operating costs by storing and accessing data as needed by utilizing scalable and dependable cloud infrastructure. Establishing precise standards and procedures for handling underwriting data throughout its lifecycle requires the implementation of strong data governance practices. This include creating guidelines for data quality, assigning roles and duties, and maintaining access controls to guarantee that only individuals with the proper authorization can access sensitive data. Furthermore, maintaining legal compliance and protecting customer privacy depend on compliance with regulatory regulations like GDPR, HIPAA, and PCI-DSS. In order to prevent unauthorized access or disclosure of sensitive data, insurers must put in place the proper security controls, encryption methods, and audit trails. Insurance companies can reduce risks and guarantee the privacy, availability, and integrity of underwriting data housed in the cloud by emphasizing data security and putting in place thorough protections. Through the process of anonymizing personally identifiable information (PII), insurance companies can lower their exposure to data breaches and lessen the possible consequences of security disasters. To identify and address possible risks quickly, cloud infrastructure must be routinely audited and monitored for security flaws and unauthorized access attempts. This entails putting intrusion detection systems into place, checking for vulnerabilities, and routinely going over access logs to spot unusual activity. Underwriting data saved in the cloud can be kept secure, intact, and readily available by insurers by prioritizing data security and putting in place extensive measures.

4. RESULT AND DISCUSSION

4.1. Experimental Setup

The proposed model CRAL is implemented and compared with existing model CNN, RNN, ANN, and LSTM.

4.2. Dataset Description

The Sample Insurance Claim Prediction Dataset [19] 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 CRAL	97.45	96.71	97.26	97.74
CNN	92.31	91.86	91.90	92.31
RNN	92.07	91.13	91.87	91.94
ANN	91.56	91.05	91.51	90.83
LSTM	87.84	86.84	86.82	86.88

A detailed comparison between the CNN, RNN, ANN, and LSTM models and the suggested CRAL model is shown in Table 1. The comparison is predicated on important performance indicators such as specificity, F1 score, accuracy, and precision. In terms of all measures, the suggested CRAL model performs better than the current models. It successfully classifies occurrences into their appropriate classes with an astounding accuracy of 97.45%. This outperforms all other models in terms of accuracy, indicating how well the CRAL architecture captures complex patterns and subtleties in the data. The CRAL model scores 96.71% in terms of precision, demonstrating its ability to correctly identify actual positive instances while reducing false positives. This high precision score demonstrates how well the model can differentiate between classes and reduce the number of misclassifications. Comparably, the F1 score of 97.26%, which indicates how well the model balances recall and precision, is achieved by the CRAL model. This score reflects the model's resilience in obtaining high recall and high precision, both of which are essential for consistent classification performance. Furthermore, with a specificity of 97.74%, the CRAL model shows that it can accurately detect actual negative instances while avoiding false alarms. The usefulness of the model in precisely recognizing occurrences of the negative class is highlighted by its high specificity. These models don't perform as well as the CRAL model, although obtaining good ratings in terms of accuracy, precision, F1 score, and specificity.

4.4. Graphical Representation of Existing and Proposed Model

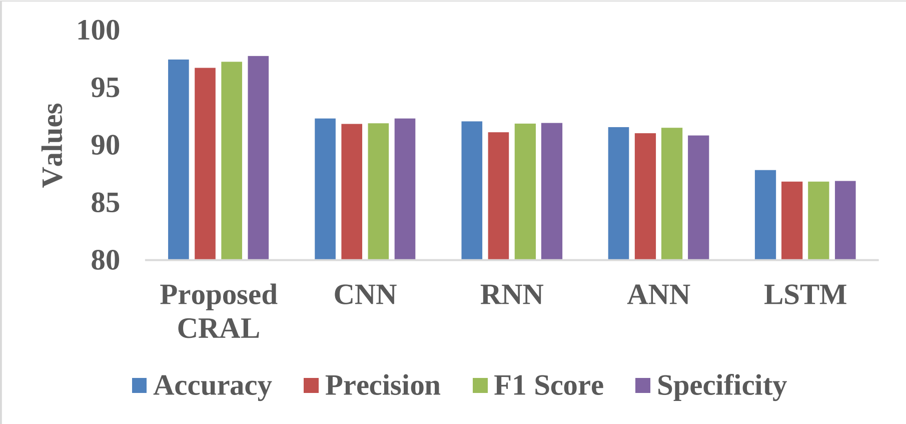

Figure 3: Existing and Proposed Graphical Representation

The graphical representation contrasting the suggested and current models is shown in Figure 3. Various evaluation metrics, including accuracy, precision, F1 score, and specificity, are represented by the x-axis, and the associated scores are shown by the y-axis. When compared to the current model, the graphical depiction amply demonstrates the suggested model's improved performance across all metrics. This graphic clearly illustrates the improved efficiency and efficacy of the suggested methodology for insurance underwriting.

5. CONCLUSION

The insurance sector was changed by the incorporation of cloud platforms into AI-driven underwriting processes, which improved decision-making and risk assessment accuracy and efficiency. With an emphasis on data collection, pre-processing, feature extraction, model selection, evaluation, validation, ongoing monitoring, and data storage, this article examined the use of cloud-based technologies in the underwriting process at several phases. Thorough data collection guaranteed the accuracy and applicability of the information, while preprocessing procedures took care of problems like missing numbers, anomalies, and discrepancies. Utilizing cloud capabilities for efficiency and scalability, feature extraction techniques like LDA, as well as data normalization and standardization, improved data for analysis. By processing sequential data and finding intricate patterns, advanced AI models including CRNN, ANN, and LSTM were introduced into the model selection process, enhancing underwriting accuracy. Over time, the resilience and reliability of the model were guaranteed by evaluation, validation, and constant observation. Data governance compliance, scalability, and accessibility were all made easier by safely storing data on the cloud. Insurance companies reduced procedures, successfully reduced risk, and eventually improved the caliber of underwriting choices by utilizing cloud platforms for AI-driven underwriting.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Not Applicable

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[18] Image taken from: “https://vitalflux.com/underwriting-machine-learning-models-examples/”.

[19] Dataset taken from: “https://www.kaggle.com/datasets/easonlai/sample-insurance-claim-prediction-dataset”, dated 2-3-2024.