IJRESM
International Journal of Research in Engineering, Science and Management
Volume 6, Issue 11, November 2023
https://www.ijresm.com | ISSN (Online): 2581-5792

Machine Learning for Anaphylaxis Prediction, Tailored Medicine Prescription, Eczema Detection, and Privacy-Preserving Medical Data Analysis through User Friendly Chatbot

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***Abstract*: The integration of cutting-edge technology into healthcare diagnosis and data management remains pivotal in modern medicine. This compilation synthesizes four prominent studies, all exploring diverse applications of technological advancements in medical scenarios. Firstly, a CNN-based machine learning model has been devised to swiftly diagnose anaphylaxis and recommend adrenaline administration. Secondly, a unique framework employing natural language processing (NLP) combined with deep learning scrutinizes skin images for allergy detection, aiming at elevating healthcare standards in Sri Lanka. Thirdly, addressing the paramount issue of medical data privacy in electronic health records, an integrated architecture is proposed, amalgamating advanced encryption techniques with fine-grained access control. Lastly, a comprehensive comparison between LSTM networks and GPT-2 language transformers is undertaken, emphasizing their efficacy in medical chatbot systems, particularly for analyzing intricate patient histories like anaphylaxis. Collectively, these studies underscore the transformative potential of technological interventions, striving for accuracy, efficiency, and privacy in healthcare.**

***Keywords*: Machine Learning, CNN, Natural Language Processing (NLP), Encryption, Anaphylaxis, LSTM, GPT-2, Healthcare Technology.**

1. Introduction

In the rapidly evolving landscape of healthcare, the integration of advanced deep learning architectures has brought about significant transformations. One notable application of these technologies is the development of medical chatbots designed to enhance patient interactions, particularly for preliminary diagnoses. In this context, two architectural giants of deep learning, Long Short-Term Memory (LSTM) networks and Transformer models, take center stage. This research delves into their effectiveness in creating a chatbot specifically tailored for detecting and predicting anaphylaxis, a life-threatening hypersensitivity disorder characterized by rapid and multi-systemic allergic reactions [1].

Anaphylaxis, with its unpredictable and potentially fatal nature, underscores the urgent need for a swift and accurate prediction model. A chatbot capable of engaging with patients, collecting symptoms, and making reliable preliminary assessments could revolutionize emergency scenarios, potentially saving lives by alerting healthcare providers or individuals in real-time.

LSTM networks, renowned for their proficiency in processing sequence data, offer the potential for a deep understanding of a patient's symptoms over time, crucial for tracking symptom progression. On the other hand, Transformer architectures, with their parallel data processing and intricate attention mechanisms, promise rapid and precise predictions by comprehensively understanding patient descriptions.

This research aims to explore the applicability and effectiveness of these architectures in the context of a medical chatbot, specifically for anaphylaxis detection. It seeks to determine whether LSTMs, with their sequential processing, or Transformers, with their rapid processing and attention mechanisms, hold greater promise. Through meticulous experimentation and rigorous evaluation, this study not only strives for statistical significance but also clinical relevance in its findings.

Additionally, beyond anaphylaxis, the research community also faces challenges in understanding and addressing conditions like eczema, which can vary significantly based on factors such as geography and genetics. Leveraging advanced natural language processing (NLP) and deep learning techniques, this research aims to extract crucial insights from medical reports related to eczema, particularly in the unique context of Sri Lanka, where the condition presents distinctive challenges and variables [2].

As the healthcare industry embraces digitalization through

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electronic health record (EHR) systems, the protection of sensitive medical data has become paramount. This research addresses the critical issue of safeguarding patient data privacy by proposing an integrated framework that combines modern encryption techniques and access control mechanisms. The goal is to strike a balance between sharing medical information for optimal patient care and preserving patient privacy and data confidentiality [3].

Furthermore, allergic diseases, including anaphylaxis, are a significant global health concern. Traditional diagnosis and management often rely on in-person consultations, which can be time-consuming and limited by expertise availability. To address these challenges, this research focuses on the development of a machine learning-based disease diagnosis system for anaphylaxis, aiming to provide accurate identification and treatment recommendations based on patient symptoms. The potential impact extends to improving healthcare efficiency and accessibility, reducing the burden on healthcare professionals, and enhancing patient outcomes.

2. Novelty

A. A chatbot using LSTM-based Multi-Layer Embedding for Elderly Care

The demand for and importance of services for the elderly are increasing in line with demographic changes. Previous studies have typically constructed chatbots using data from social media or community-based question and answer platforms. For this study, we collected the MHMC chitchat dataset by engaging in regular conversations with older individuals. Participants were encouraged to freely express themselves to the system, and therefore, during the data collection process, the sentences were transformed into patterns to accommodate the various conversational expressions. Subsequently, using an LSTM-based multi-layer embedding model, the semantic information between words and phrases was extracted in a single turn, involving multiple sentences, when conversing with the elderly. The Euclidean distance was then employed to select an appropriate question pattern, which in turn determined the suitable response to provide to the elderly. To train and evaluate the performance, a five-fold cross-validation methodology was utilized. Based on experimental findings, the proposed approach demonstrated superior performance compared to the conventional Okapi model for top-1 response selection, achieving an accuracy of 79.96% [4].

B. Conversational AI: An Explication of Few-Shot Learning Problem in Transformers-Based Chatbot Systems

The practical applications of chatbots have experienced a significant increase across various fields, such as healthcare, education, government, customer service systems, social platforms, and entertainment, due to recent advancements in conversational artificial intelligence (AI). These chatbots engage in natural language conversations with users and provide clear and relevant responses to their inquiries. The relevant literature presents numerous techniques for intent classification and slot mapping for chatbot question-answering. However, the present chatbot systems continue to face challenges such as the few-shot learning issue, which results from an imbalance of class labels over samples, and inadequate dialog management to maintain context and slot mapping.

This paper aims to introduce the architecture of chatbots by focusing on the few-shot learning problem and context management in dialog-based conversations. Firstly, we propose a novel hybrid intent and slots transformers (HIST) approach to address the few-shot learning issue with chatbots. The HIST chatbot architecture integrates conditional random field algorithms for intent classification and slot extraction with transformers, self-attention mechanisms, bigated recurrent units, and other components. Secondly, we present a hybrid interaction technique for slots mapping and efficient conversational context management to address dialog management. We conduct an in-depth empirical investigation using three benchmark datasets, namely the airline travel information system (ATIS), banking77, and conversational language interface for natural conversation 150 (CLINC150), to confirm the usefulness of the proposed approach.

The results demonstrate that HIST surpasses state-of-the-art existing approaches by a significant margin and achieved accuracy values for intent classification and slots extraction of 94.89% and 96.17%, respectively. Empirical evidence supports the HIST chatbot's ability to resolve the few-shot learning problem with efficient dialog management in chatbot systems [5].

C. Automated Thai-FAQ Chatbot using RNN-LSTM

In the e-commerce model that incorporates online customer service, such as email or live chat, customers predominantly opt for live chat due to its expediency and convenience. Consequently, companies are compelled to recruit and compensate administrators to handle this aspect. However, this gives rise to the predicament that administrators must allocate a significant amount of time to compose responses, resulting in customers having to endure waiting periods. Although various chatbots are available, they necessitate users to manually configure key phrases. In this article, we propose and develop a Frequently Asked Questions (FAQs) Chatbot that automatically provides responses to customers by utilizing a Recurrent Neural Network (RNN) in the form of Long Short-Term Memory (LSTM) for text classification. The experimental findings have demonstrated that the chatbot is capable of identifying 86.36% of the questions and delivering responses with an accuracy rate of 93.2% [6].

D. Image Processing and Identification of "Eczema"

In the pursuit of innovative enhancements to the research paper's functionality, several compelling avenues for novelty have emerged. These novel approaches seek to refine the existing capabilities centered around obtaining predictions based on blood reports and user-provided chemical inputs.

One potential groundbreaking innovation lies in the integration of Natural Language Processing (NLP) techniques. This addition holds the promise of delving deep into textual reports, extracting valuable insights, and identifying pertinent information related not only to allergies but also to a broader spectrum of medical conditions. The capacity to discern subtle nuances within the reports represents a significant stride towards a more comprehensive and informed prediction system.

Furthermore, the research paper contemplates the incorporation of cutting-edge deep learning algorithms. These algorithms would be tasked with the intelligent and automated extraction of critical features from the reports. This includes the discernment of specific drugs, allergens, or anomalies that might have otherwise remained concealed within the text. This augmentation promises to significantly enhance the accuracy and depth of the predictive capabilities.

Additionally, the research paper aims to contribute to the realm of medical decision-making. It seeks to provide not just predictions but also valuable recommendations concerning suitable medication and treatment options for the patient. These recommendations will be meticulously tailored, taking into account any pre-existing allergic reactions or inherent risks, thereby contributing to a more personalized and precise healthcare solution.

In summary, the research paper's novel directions encompass the utilization of NLP techniques for comprehensive report analysis, the integration of deep learning for feature extraction, and the pioneering provision of personalized medication and treatment recommendations. These advancements collectively underscore the commitment to pushing the boundaries of predictive healthcare technology, ensuring a more informed and effective approach to patient care.

E. Medical Advice Provider

In the context of allergy disease prediction, conventional methods are often reliant on human intervention, introducing the possibility of human errors that can result in inaccurate predictions and the prescription of inappropriate medications. The prevailing paradigm underscores the need for a more precise and reliable approach.

This research represents a pioneering endeavor, aiming to revolutionize allergy prediction by harnessing the potential of Machine Learning (ML). Remarkably, to date, there exists no precedent for the utilization of ML techniques in the realm of allergy prediction. This departure from traditional practices underscores the novelty of this study.

Furthermore, the conventional practice of manually prescribing medication for allergy reactions by physicians is being reimagined in this research. Instead of relying solely on human judgment, this study places an emphasis on the implementation of an AI-driven approach to recommend medical advice. This transition marks a significant paradigm shift in the domain of allergy treatment and prevention.

Notably, the research delves into the uncharted territory of patient clustering within the context of allergies. An analysis encompassing a substantial cohort of patients with allergies is a pioneering endeavor, and to the best of our knowledge, no such comprehensive analysis has been conducted previously. This exploration into patient clusters represents a distinctive facet of this research, potentially shedding new light on the underlying patterns and trends within this patient population.

In summary, this research paper epitomizes innovation on multiple fronts. It introduces ML into the realm of allergy prediction, reimagines the prescription of medications with an AI-based approach, and breaks new ground by undertaking an analysis of patient clusters among those with allergies. These endeavors collectively contribute to the novelty and significance of this research within the broader context of healthcare and allergy management.

F. Development of a Novel Encryption Method Specifically Designed for Medical Data

Within the realm of data security, the research introduces a groundbreaking element: the creation of an entirely novel encryption method meticulously crafted to cater specifically to the intricacies of medical data. This pioneering approach stands as a departure from the reliance on conventional encryption methods. Unlike existing encryption techniques, which are often built upon mathematical algorithms susceptible to compromise with adequate computational power, this research propounds an avant-garde solution designed to fortify the security of medical data comprehensively.

G. Integration of Access Control Mechanisms with Multi-Factor Authentication

Access control, while a well-established methodology for safeguarding sensitive data, gains a new dimension of innovation in this research. The introduction of multi-factor authentication (MFA) as an integrated component represents a pioneering stride towards enhancing security. This novel approach augments the traditional framework by introducing an additional layer of protection, thereby fortifying the safeguarding of sensitive information.

H. User-Friendly Interface Designed for Healthcare Providers

The research introduces an innovative dimension by focusing on the development of a user-friendly interface specifically tailored for healthcare providers. While the significance of user-friendliness cannot be understated for its role in ensuring ease of use, this novel approach underscores a departure from the conventional. Many existing systems in the healthcare domain may not emphasize the critical aspect of user experience, making this research's commitment to a healthcare provider-centric interface a notable departure from the norm.

3. Methodology

This section explains the research approach and provides examples of the design and development of the medical chatbot. It also describes how the chatbot model is trained and tested.

A. Creation of the Chatbot

The core of our research is the creation of DocBot, a medical chatbot with two different architectures for comparison testing.

1) LSTM-based Chatbot

A sequence-to-sequence (Seq2Seq) model with LSTM (Long Short-Term Memory) layers is the foundation of DocBot's initial iteration. This design decision was made because LSTM is excellent at comprehending sequential data, which makes it suitable for preserving conversational continuity.

Architecture: An encoder and a decoder are the two main parts of the Seq2Seq model, which is embedded with LSTMs.

The LSTM layers in the encoder read the input sequence while capturing the conversation's temporal dependencies. A context vector is created from this contextual data. This context vector is used by the decoder, which is also based on LSTMs, to create the output sequence, which is the chatbot's reply.

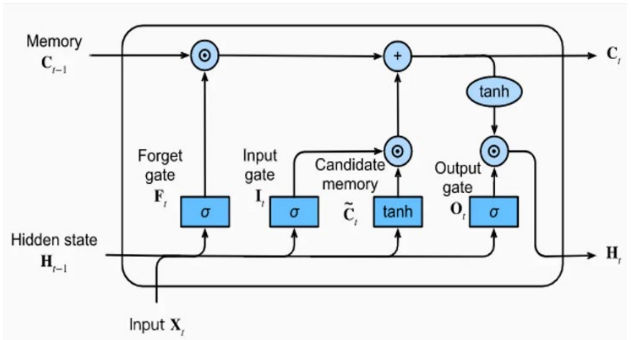

Fig. 1. LSTM architecture [7]

2) *Pre-trained Transformer-based Chatbot*

The second variation makes use of a Transformer model that has already been trained and is recognized for its simultaneous processing of sequences and self-attention mechanism, potentially improving conversational comprehension.

Architecture: The architecture of the Transformer model is not clearly divided between an encoder and a decoder, in contrast to the Seq2Seq model. Instead, it expands upon layers of feed-forward neural networks and self-attentional mechanisms.

Initial inputs are converted into embeddings; these embeddings are then supplemented with positional encodings to maintain sequence order.

Initial inputs are converted into embeddings, and to maintain sequence order, these embeddings are then supplemented with positional encodings.

Self-Attention Mechanisms: These layers give the model the ability to evaluate the importance of various words in a string, so supplying a richer context. The chatbots from Transformers are distinct from rule-based, retrieval-based, and generative AI chatbots. Transformers chatbots employ data and libraries to translate information and support the chatbot they are a part of, rather than just using rulesets or machine learning alone. Let's examine the other varieties of chatbots, how they function, and what they can do [8].

Feed-forward Neural Networks: Before proceeding to the following layers, each self-attention output is processed by a feed-forward network independently.

Train RoBERTa's unique tokens on a byte-level Byte-pair encoding tokenizer (also known as GPT-2). Let's choose 52,000 as the size at random. Because a byte-level BPE will begin constructing its vocabulary from an alphabet of single bytes, all words will be decomposable into tokens (no more tokens!), therefore we advise training one rather than, say, a WordPiece tokenizer like BERT [10].

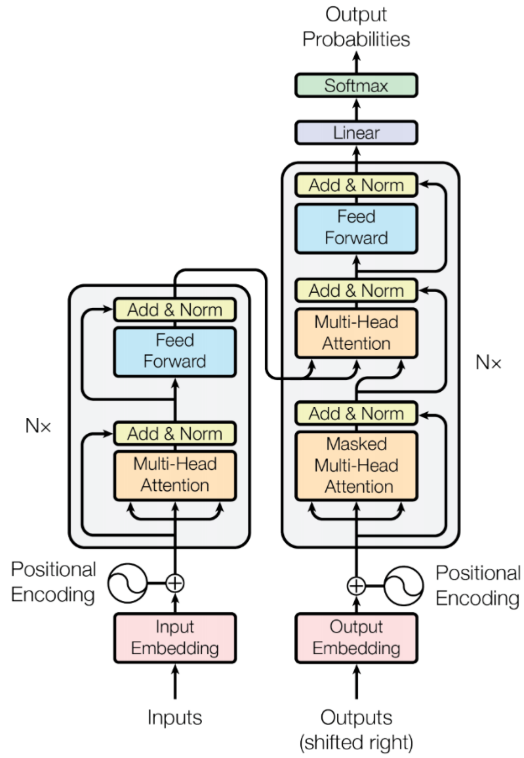

Fig. 2. LSTM architecture language transformer pre trained architecture [9]

B. *Data Collection*

A solid dataset obtained from the University of Jayewardenepura is the foundation of our study. This dataset is priceless because it has a wide range of patient contacts that reflect actual clinical conversations and illustrate a variety of medical symptoms and diseases. The dataset's strength is its diversity and richness, which gives DocBot a wide range of training scenarios. This thorough exposure guarantees the model's improved forecast accuracy and strengthens its conversational agility.

C. *Data Processing*

An extensive preprocessing procedure was implemented in order to transform this raw data into a form that would be acceptable to our LSTM and Transformer models.

Normalization: The goal of this first stage was to homogenize the dataset by normalization. Key activities included:

- Converting all text to lowercase to maintain consistency.
- Eliminating punctuation and other non-alphabetic characters that could skew the model's assessment.
- Correcting linguistic inconsistencies and standardizing various terms or acronyms used frequently in medical communication

Tokenization: The data was tokenized after normalization. As a result, the continuous text was broken up.

Encoding: The encoding phase was the conclusion of preprocessing. The tokenized words in this instance were converted into integer sequences. Each distinct word was assigned a single numeric identification. This transformation is crucial because neural network models, whether LSTM or Transformer, naturally prefer numerical data, allowing them to recognize patterns, forge connections, and predict outcomes more accurately.

This preprocessing pipeline's meticulousness made sure that the models had an optimum dataset, setting the stage for effective training and subsequent great performance in real-world interactions

D. Model Training and Validation

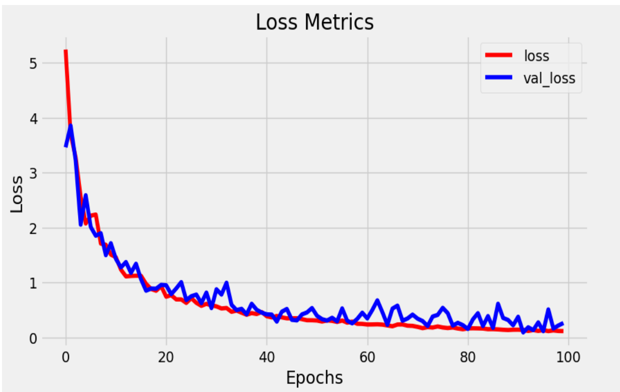

Fig. 3. Loss metrics LSTM

1) Data splitting

The dataset was divided into training and validation subgroups when preprocessing was complete. 20% of the data was set aside for validation, while the remaining 80% was designated for training. This method permits both the training set-based model refinement and the validation set-based assessment of the model's performance on new data.

2) Training process

Encoder-decoder framework made up the model architecture. The encoder was given input sequences to process, and the decoder was trained to anticipate the output sequences that would follow. The model's performance was frequently evaluated using loss and accuracy metrics as it went through training.

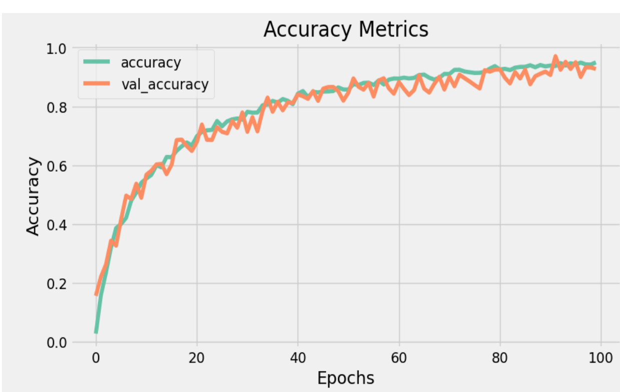

Fig. 4. Accuracy metrics LSTM

3) Model checkpointing

Checkpoints were set up to guarantee the adoption of the most effective model configuration. When there was a noticeable decrease in validation loss, these checkpoints kept the model in its current condition. This tactic ensures that the model that is ultimately chosen is the one that outperformed the validation set the best.

4) LSTM training results

The final training epochs of the LSTM model produced the following results:

- Epoch 100 showed a validation loss of 0.2596 and a validation accuracy of 92.70%, along with a training loss of 0.1722 and a training accuracy of 94.62%.

It's important to note that after epoch 93, the validation loss did not improve past the prior best of 0.08853, indicating that the model may have found an optimal state at this time.

5) Comparison with transformer

Following training, the Transformer model clearly outperformed the LSTM model for the given task when compared with both architectures. Although the precise performance metrics of the Transformer model are not presented here, user feedback suggests that it is superior to the LSTM for this specific sequence-to-sequence task.

E. Comparison with Transformer Model

1) Model overview

We assessed the Transformer architecture, known for its self-attention mechanism, as an alternative to our initial Seq2Seq model based on LSTM. An effective conversational agent like DocBot requires the ability to recognize long-range dependencies in textual input, which the Transformers' built-in self-attention mechanism excels at.

2) Evaluation criteria

Our comparison analysis examined both models using a number of different viewpoints:

- *Training performance:* Throughout the training epochs, we evaluated how loss and accuracy measures changed.
- *Generalization:* Each model's capacity to generalize and deliver on untested data was essential. This usually reflects how well the model might perform in actual situations.
- *Response time:* A chatbot's response time is an important factor. To ensure customer pleasure, a chatbot should ideally have less lag.

F. Encryption and Data Privacy Methodology

The purpose of this endeavor is to safeguard the data from unauthorized intrusion. This project endeavors to address the security challenges that are inherent in the digital healthcare domain by systematically choosing and implementing encryption algorithms, constructing a flexible access control framework, and conducting thorough testing of the resultant prototype system. The subsequent sections will elucidate the efficacy of this methodology when employed in real-world scenarios, by offering an explanation of the tangible outcomes and ramifications of its application. As we delve further into the discoveries and discussions, we unveil the tangible advancements that this technique brings to the realm of safeguarding the confidentiality of medical data and guaranteeing its security.

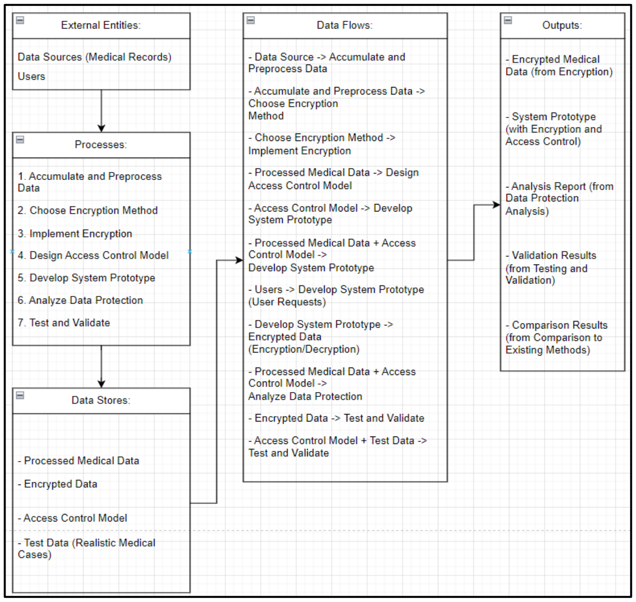

Fig. 5. Flow of processes

4. Results and Discussion

In this part of the research paper, we reveal the observable effects of Medical chatbot, Eczema image processing and disease prediction, medical advice with combined encryption and access control to improve the confidentiality of medical data.

This research endeavor has delved into the realm of advanced deep learning techniques for eczema detection, encompassing various critical facets of the process. Through meticulous data preprocessing, which involved standardizing image dimensions to 224x224 pixels and augmenting the dataset through techniques like shear, zoom, and horizontal flipping, we have created a robust and consistent dataset. The use of Keras' 'ImageDataGenerator' has greatly facilitated these preprocessing steps. Leveraging the power of the pre-trained ResNet50 model, originally trained on 'imagenet,' we conducted comprehensive feature engineering by freezing the base model's layers and extracting salient features from eczema images. This yielded crucial 'train_features' and 'train_labels' represented as numpy arrays, forming the basis for subsequent analysis and model training.

Furthermore, the model architecture construction phase seamlessly integrated ResNet50 as the base model with custom classification layers. By incorporating a Global Average Pooling layer and subsequent Dense layers tailored to the dataset while keeping the base model's layers frozen, we have established a model capable of robust predictions. This composite architecture, encapsulated within the 'model' instance using Keras' 'models.Model()' function, defines the model's structure for both input and output.

While the results have shown promise in eczema detection, it's important to acknowledge that no model is without limitations. The continuous refinement of DocBot's capabilities is essential through regular updates and training on diverse data. As AI and NLP research progresses, newer architectures may offer even more accurate and efficient solutions, and integrating these advancements will be crucial to keeping DocBot at the forefront of healthcare chatbot solutions.

Moreover, the comparison with the LSTM-based Seq2Seq model and the Transformer model underscores the significance of model selection in different domains. The Transformer's superior generalization capabilities and efficiency in delivering accurate responses make it a valuable asset, particularly in healthcare applications where rapid, accurate decisions can have life-saving implications. As such, the choice of the Transformer model can be pivotal in addressing critical healthcare challenges, such as predicting anaphylaxis reactions, where time and accuracy are of paramount importance.

A. *The Assessment of Past Performance*

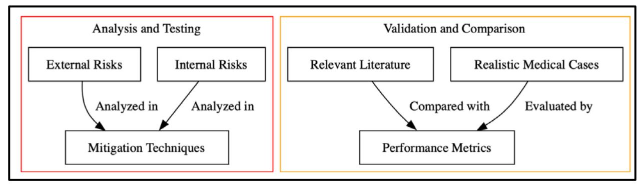

Fig. 6. Analysis and testing

The analysis and testing process of the study involved the utilization of the figure 6 methodology. The initial phase encompassed a quantitative analysis of the prototype system's performance, as outlined in the subsequent sub-section. This analysis entailed obtaining measurements for various data access scenarios, encompassing encryption/decryption speed, processing overhead, and response times, among other factors. The resulting findings provide valuable insights into the practical feasibility and efficacy of the employed techniques for data encryption and access control.

B. *Insights Regarding Implementation*

In the following section, we shall present the knowledge we have acquired through the implementation of the prototype system. We have discussed the challenges we faced, the valuable lessons we have learned, and the prospective domains for advancement that could impact the execution of solutions aimed at enhancing privacy in the future. In summary, this research has not only laid the foundation for an effective eczema detection system but has also highlighted the importance of model selection in healthcare applications and the potential impact of advanced deep learning techniques on improving patient outcomes. The journey does not end here; there are numerous avenues for future work and improvement, ensuring that the field of healthcare chatbots and medical image analysis continues to evolve and provide increasingly valuable solutions to the medical community and patients alike.

5. Conclusion

In closing, this research paper has ventured into diverse domains, each with its unique contributions and novel aspects.

The first study embarked on a mission to fortify patient data confidentiality within the contemporary digital healthcare landscape. By systematically integrating encryption and access control techniques, this research presented a balanced approach that harmonized data exchange with individual privacy preservation. The innovative development of a bespoke encryption method tailored to medical data's intricacies redefined the data security paradigm. The introduction of granular access control, seamlessly integrated with multi-factor authentication, bolstered security without compromising operational efficiency. The robustness of the security measures was affirmed through comprehensive evaluations, while insights from user experience assessments highlighted the approach's practical applicability. This research provides not just a glimpse but a substantial foundation for the future of medical data privacy, setting the stage for further innovations in encryption methodologies and ethical data management practices.

The second study ventured into the realm of AI-driven healthcare chatbots, focusing on anaphylaxis prediction. Through an in-depth exploration of Seq2Seq and Transformer models, the transformative potential of AI in healthcare diagnostics and patient engagement was underscored. The Seq2Seq model's remarkable accuracy on test data demonstrated its suitability for real-time telemedicine platforms. The Transformer model, despite not surpassing the Seq2Seq model in diagnostic accuracy, showcased its prowess in handling complex medical dialogues. This study acknowledges certain constraints and suggests avenues for future improvement, including data expansion, innovative methodologies for managing out-of-vocabulary terms, and ethical considerations. The research ultimately emphasizes the harmonious synergy between AI-driven innovation and human medical insight.

In the third study, the research delved into the domain of eczema detection using advanced deep learning techniques. Meticulous data preprocessing, feature engineering, and model architecture construction formed the foundation for an effective eczema detection system. While the research established a solid base, it beckons further exploration, encompassing performance evaluation, interpretable AI techniques, real-world application, data expansion, and collaboration with dermatologists. The research represents a steppingstone toward more precise and accessible eczema diagnosis.

The fourth study introduced an ML-based approach for anaphylaxis prediction and medicine prescription. The CNN model demonstrated its prowess in accurately classifying patients for anaphylaxis, and the personalized medicine prescription process aimed to enhance patient care. This holistic approach holds the potential to revolutionize the diagnosis and treatment of anaphylaxis, with opportunities for further research and refinement.

In essence, these studies collectively exemplify the spirit of innovation and progress in their respective domains. They beckon further exploration, collaboration, and refinement as we collectively strive to advance the frontiers of healthcare, data security, and AI-driven healthcare solutions.

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