Chapter 1

ON THE DEVELOPMENT OF A COMPUTATIONAL MODEL FOR SPECIALIST PHYSICIAN RECOMMENDATION USING HISTORICAL PATIENT DATA IN A PRIVATE CLINIC

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Abstract

This study explores the application of artificial intelligence (AI) in healthcare, with a particular focus on predictive analytics. Despite lofty expectations, the impact of AI in healthcare has been less pronounced than anticipated. The study aims to develop a predictive model using AI to recommend suitable healthcare professionals to patients. This model utilises exploratory data analysis, recommendation systems, and datasets. The objective is to augment the role of predictive analytics in medicine, potentially revolutionising the processes of disease treatment and diagnosis. The research underscores the pressing need to harness the full potential of AI in healthcare, countering its currently limited influence.

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1 INTRODUCTION

In Brazil, health is a critical issue across social, political, and economic spheres. While the Federal Constitution guarantees health rights, these are often not fully realised [22]. Achieving adequate health capacity remains a challenge, necessitating state health system restructuring and exploring new healthcare alternatives. In the 1960s, many Brazilian companies started providing medical services to employees due to public health inadequacies,

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leading to the emergence of group medicine companies [12]. By 1997, these served over 17 million people, with medical cooperatives becoming a notable model. A study showed private healthcare as the main expense for Brazilian families from 2010 to 2017, with the government spending R$ 608.3 billion on healthcare in 2017 [13]. The uneven distribution of doctors, primarily in urban areas, exacerbates healthcare quality issues [23].

Long wait times for medical appointments significantly impact patient outcomes, serving as a health system responsiveness indicator [14]. In Brazil, these delays, compounded by chronic diseases and resource shortages, are major barriers to comprehensive healthcare [3].

This context requires technological solutions like artificial intelligence-based systems (AI) to analyse patient symptoms and history for appropriate medical specialty recommendations, aiming to reduce wait times and symptom aggravation [9]. AI, with its advanced analysis and machine learning capabilities, addresses real-world challenges effectively [1]. This research focuses on developing a computational model to optimise patient referrals to medical specialties, integrating clinical feedback for more accurate and efficient recommendations [27]. This approach underscores the potential of AI in transforming healthcare quality and efficiency, highlighting the need for healthcare professionals to embrace such innovative technologies.

The rest of this chapter is organised as follows: Section 2 provides an overview of the literature by analysing the related works; Section 3 describes the materials and methods adopted to conduct this research; Section 4 introduces the computational model we have developed for decision making in healthcare; Section 5 discusses the main results; and, Section 6 concludes this chapter.

2 RELATED WORK

In contrast to our approach, Jameel et al. [8] employ an Artificial Intelligence-based *chatbot* to determine the appropriate medical specialty for a patient. This chatbot is designed to interact directly with patients through natural text dialogue and extract pertinent information to direct patients to the appropriate medical specialty. However, the main limitation of this method is that it is based exclusively on direct interaction with the patient and does not take into account the patient's medical history. While the use of a *chatbot* can provide a user-friendly and interactive interface for patients, the lack of an in-depth examination of the patient's medical history can limit the accuracy of the referral to the medical specialty. Our approach, on the contrary, combines the practicality of direct interaction with the patient with the depth of a complete analysis of the medical history, providing a more robust and comprehensive system for directing patients.

The study carried out by Huang et al. [6] proposes an algorithm for recommending doctors, based on the doctors' performance model and the patient's preferences model. This aims to alleviate the problem of doctors' information overload and the "reserve imbalance" on the Shanghai Medical League scheduling platform, helping patients successfully book a doctor's appointment. The algorithm is designed by adding the feature of patient preferences to the doctors' performance model, which is built with the Hierarchical Analytical Process method. Currently, the recommendation algorithm has already been successfully applied to the Shanghai Medical League Scheduling Platform. The algorithm is evaluated by patients' operation records and reservations, and the results show that the recommendations are reasonable and can effectively meet patients' reservation demands. However, this study focuses on scheduling appointments, whereas our approach addresses determining the appropriate medical specialty based on a detailed medical history. Therefore, although this study's approach is useful for scheduling appointments, it may not be in-depth enough to determine the most appropriate medical specialty for a patient.

In another relevant study by Meng and Xiong [15], a doctor recommendation technology is proposed to help patients filter a large number of doctors with unsuitable specialties and find those who meet their real needs quickly, helping them access personalised and beneficial healthcare services online. To solve the problems with existing recommendation methods, this work proposes a hybrid doctor recommendation model based on an online healthcare platform, which uses the *word2vec model*, the Latent Dirichlet Allocation (LDA) topic model, and other methods to find doctors who best meet patients' needs, with information obtained from consultations between doctors and patients. The model considers these doctors as nodes to build a doctor tag network and recommends the most important doctors in the network through an eigenvector centrality calculation model on the graph. This method identifies the important nodes in the network of effective doctors to support the recommendation from a new graph calculation perspective. An experiment conducted on the Chinese health website [1] proves that the proposed method has good recommendation performance. The work presents a sophisticated and effective methodology for recommending doctors based on previous consultations, however, it differs from our proposal as it does not take into account the patient's detailed medical history to determine the most appropriate medical specialty. Our proposal seeks to make use of deeper, contextualised information to make a more accurate recommendation of the medical specialty needed.

The study proposed by Gujar et al. [5] proposes an adequate analysis of clinical documents related to patients' health to anticipate the possibility of the occurrence of various diseases. Additionally, obtaining information from disease-specific specialists as needed facilitates proper and efficient diagnosis. Their work offers an innovative method that uses a data mining technique, more specifically, the Naive Bayes classification algorithm for disease prediction followed by expert recommendation on the predicted disease. Using medical profiles like heart rate, blood pressure through sensors and other externally observable symptoms like fever, cold, headache etc., that the patient has, the probability of a disease is predicted. The Naive Bayes algorithm takes these symptoms and predicts the disease. Furthermore, all necessary and appropriate information about the anticipated illness and recommended doctors are provided. The recommendation suggests location, contact, and other necessary details of disease experts based on user-chosen filters such as lowest rate, most experience, closest location, and feedback ratings of doctors. Ratings are compared using Stanford's CoreNLP algorithm. So the user can get proper treatment and necessary medical advice as quickly as possible. Additionally, users provide feedback to recommended doctors, who are then added to the analysis to make future recommendations based on the reviews. The work presents a robust and efficient method for predicting diseases and recommending doctors, although it is different from our proposal, as the main focus is on predicting diseases based on symptoms and vital signs and not on determining

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the most appropriate medical specialty based on the patient's detailed medical history. In our proposal, we seek to leverage deeper, more personalised information to provide a more accurate recommendation of the medical specialty needed.

3 MATERIALS AND METHODS

This section details the research's materials, methods, AI model development process, data collection, analysis techniques, and methodological choices.

3.1 Tools

The AI model was developed using Python programming language and the Scikit-learn machine learning library, chosen for their syntax clarity, extensive libraries, and familiarity. Additionally, Pandas software tool was used for data manipulation, Matplotlib and Seaborn for visualisation, and Jupyter Notebook for interactive development and documentation. The model training and evaluation utilised a high-capacity computational environment with advanced CPUs, RAM, and data storage capabilities.

3.2 Dataset

Data were sourced from various medical and health databases, including electronic medical records, examination databases, prescription databases, and medical referral records. These were gathered from diverse hospitals and clinics, ensuring data diversity and representativeness. All data were anonymised for patient privacy protection. The dataset contains patient medical histories, symptoms, prior diagnoses, treatments, and other pertinent factors, crucial for training the AI model to pinpoint the most suitable medical specialty for each patient. Data collection complied with local ethical and regulatory guidelines. Ensuring patient confidentiality, all data were anonymised and de-identified before processing and analysis, with personal identifiers removed or altered. Data quality was a key consideration. Quality analysis was conducted to verify data integrity, accuracy, consistency, and relevance. pre-processing measures addressed missing data, outliers, and errors. The final dataset was split into training and test sets, with the former for training the AI model and the latter for evaluating model performance on previously unseen data.

3.3 AI Model

The AI model development followed an iterative machine learning cycle, encompassing data pre-processing, feature selection, model training, model evaluation, and hyperparameter tuning. Data pre-processing involved techniques to clean and transform data, including handling missing data and outliers, normalising numerical values, encoding categorical variables, and removing irrelevant or redundant variables. These steps enhance data quality and model effectiveness. Feature selection utilised correlation analysis, attribute importance, and dimensionality reduction techniques to identify variables crucial for predicting medical specialties. Various machine learning algorithms, such as logistic regression, decision trees, random forests, support vector machines (SVMs), and neural networks, were

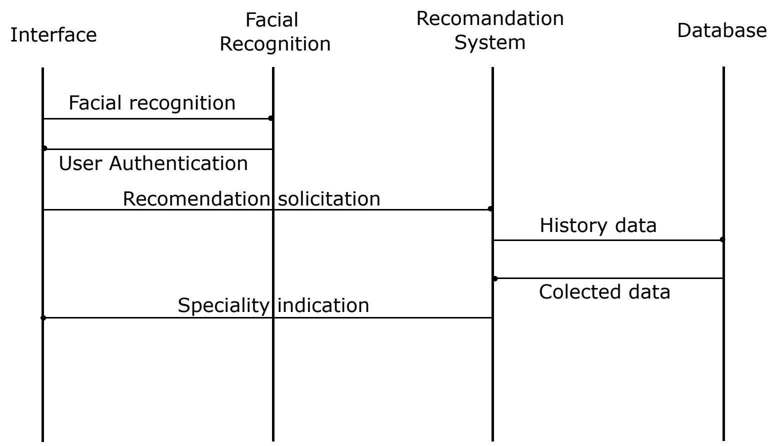

Figure 1: Module workflow.

tested during model training. The final model was chosen based on accuracy, robustness, and generalisability.

Model evaluation employed performance metrics like accuracy, recall and F1-score, providing a comprehensive assessment considering both true and false positives. Finally, hyperparameter tuning was conducted using grid search and random search techniques to optimise model parameters and enhance performance.

4 Proposed Computational Model

This section provides an overview of a proposed modular computational model designed to deliver relevant and personalised information for medical treatment patients. The model comprises three main modules, each performing specific functions. The first module is an AI system for extracting keywords from electronic prescriptions and medical exams, creating datasets from these inputs. It uses machine learning algorithms to identify relevant keywords in various medical documents, like recognising terms such as "hypertension" or "diabetes" in electronic prescriptions. The second module is a user interface service employing facial recognition technology to identify patients and collect data on their medical history and symptoms. This service detects vital information, including heart rate and blood oxygen levels, and gathers symptom details, aiding in identifying the most suitable medical specialty. The third module processes information from the first two modules to identify the most appropriate medical specialty for the patient. It analyses datasets and collected data using AI algorithms, considering symptoms, medical history, and vital data to determine the best specialty for the patient's needs, as shown in Figure 1.

This modular computational model integrates AI into healthcare, offering an innovative and efficient solution for providing patients with tailored information. Its interconnected modules using AI to extract medical document information, gather vital data, and identify the suitable medical specialty represent a groundbreaking approach in medicine, potentially improving patient outcomes and healthcare system efficiency [20]. The model's ability to evolve with new medical data and advancements ensures it continues delivering updated, personalised patient care. It also serves as a decision-support tool for healthcare professionals, assisting in correlating symptoms with medical conditions and evaluating therapeutic approaches. Implementing this model in medical institutions and health systems may face challenges like data privacy, healthcare professional training, and resistance to change. However, the benefits of this modular computational model could outweigh these challenges, transforming patient care to be more personalised, efficient, and precise.

4.1 Data Repositories

The data repositories used in developing datasets for AI application are crucial for ensuring analysis quality and precision. In our computational model, multiple databases and datasets per patient were utilised, stored in a MongoDB database. This section delves into these repositories and datasets, highlighting the importance of the MongoDB service and the integration of microservices for facial recognition and accessing patient clinical information. MongoDB, a leading NoSQL database, offers scalability, flexibility, and data availability, efficiently storing structured and semi-structured data. It's suitable for medical information, handling large data volumes, complex queries, and fast information retrieval. It supports advanced query and indexing features for real-time complex analysis. Each dataset contains clinical and historical patient information, including consultation and test details, symptoms, vital signs, and laboratory test results, crucial for individualised profiles and AI system analysis [2].

Microservices for facial recognition and clinical information access automate and optimise data analysis processes, reducing time and effort for data preparation. They are vital for the efficient interaction between different system modules and facilitate system maintenance and updates. These repositories and datasets are continuously updated with new medical information and research, ensuring the AI system's access to the latest information for identifying emerging trends and incorporating new knowledge into analysis and diagnosis. This continuous update also helps reduce data bias, enabling the AI system to provide more accurate and effective diagnostics and treatment recommendations [28].

Ensuring patient data privacy and security is paramount. Data security policies and governance practices align with data protection regulations like GDPR law. Patient information is anonymised and encrypted to maintain confidentiality and minimise information leakage risks [19]. Ensuring representativeness and diversity in datasets is crucial to avoid bias and ensure the AI system's efficiency and applicability to a wide range of patients [16]. Continuous maintenance and improvement of datasets and repositories, including data error correction and new information sources incorporation, ensure the AI system's increasing accuracy, adapting to medical field changes and advancements. Thus, these repositories and datasets are vital for analysing patient clinical and historical data, allowing for personalised profiles and models for medical monitoring and treatment. The choice of MongoDB and other NoSQL technologies provides flexibility and scalability for handling large data volumes and complexity, ensuring efficient and precise analysis.

The importance of repositories and datasets for AI application in the described computational model is evident. MongoDB's selection, integration of microservices for facial recognition and clinical information access, and ongoing data maintenance and enhancement are key to the model's success. Ensuring data privacy, security, and diversity is essential to avoid bias and ensure system applicability to a wide range of patients. The continuous focus on improving and updating repositories and datasets will ensure the development and efficacy of the computational model in medical practice, providing more personalised, efficient, and accurate diagnostics and treatments.

4.2 Dataset Generation

Generating a quality medical test dataset, excluding imaging exams, involved multiple steps and techniques to ensure information accuracy. The process had four main phases: document selection, information extraction, data cleaning and pre-processing, and dataset storage and availability [20]. Initially, patient medical exams in the database were carefully analysed and selected based on criteria like information relevance and population representativeness [30]. In the extraction phase, *pdfminer* and *textblob* libraries identified and extracted keywords and relevant information, identifying medical entities like test names, diseases, diagnostics, and related numerical values.

The extraction faced document format variability and text quality, requiring text processing techniques like special character removal, spelling correction, and tokenisation for consistency and quality. The third phase, data cleaning and pre-processing, involved using Pandas to remove duplicates, incorrect entries, blanks, and errors, re-processing standardised numerical values and transformed data for AI model analysis and training [4]. In the final phase, data was stored in a format compatible with data analysis and machine learning tools, ensuring easy access and use in future analyses and AI model training [17].

This complex task employed various data processing techniques and tools like Python, *pdfminer*, *textblob*, and Pandas, producing a high-quality dataset crucial for efficient and accurate AI models [7]. The dataset can be used in medical applications like decision support systems, trend analysis, and AI model training for diagnosis and prognosis. Its availability advances medicine and information technology, allowing significant health field progress [20]. Thus, non-imaging medical test dataset generation is essential for AI-based computational models in medicine. Proper tools and techniques for extraction, cleaning, pre-processing, and data storage ensure dataset quality and representativeness. This enables creating accurate and efficient models, improving medical care and data-driven decision-making [20].

Quality datasets and AI application in medicine can revolutionise healthcare professionals' approach. Machine learning-based computational models assist in pattern identification and new knowledge discovery, enhancing medical care quality and diagnostic accuracy [27]. Integrating these models into healthcare systems and training professionals to interpret and apply data analysis results is key to maximising technological innovations in healthcare. It's crucial to view AI-based computational models as complementary tools to healthcare professionals, offering valuable insights for decision-making and continuous medical care quality improvement [26]. Thus, generating a quality test dataset is a critical step in developing and applying AI models in medicine. The mentioned methodology, along with tools like Python, *pdfminer*, *textblob*, and Pandas, demonstrate how this process can be efficiently and automatically conducted, contributing to advancements in medicine and information technology, and facilitating significant health sector improvements.

4.3 Medical Specialty Recommendation Models Based on Clinical Exams

Implementing medical specialty recommendation models marks a frontier in contemporary medicine, serving as crucial elements in clinical decision support. These models meticulously analyse symptoms and clinical exam data, guiding towards the most relevant medical specialty. Their innovation lies in enhancing the precision and effectiveness of patient triage, optimising resources, and improving specialist referrals. Anchored in advanced machine learning and AI techniques, these models adapt and interpret the multifaceted nature of clinical data. Notably, Natural Language Processing techniques excel in deciphering intricate textual data in clinical reports, enabling more refined and contextualised recommendations. However, implementing these systems faces significant challenges. Data quality and volume, interpreting unstructured clinical information, and integrating these models into existing healthcare infrastructures require innovative and meticulous solutions.

Various models contribute significantly to the field, employing diverse computational and algorithmic techniques for clinical data interpretation and analysis, aiming for more accurate and contextual medical recommendations. The transformative potential of medical recommendation models in clinical practice is undeniable, reshaping patient triage paradigms. Yet, this transformation involves complexities in ethics, privacy, and systemic integration, necessitating ongoing research and development and a robust understanding of the health ecosystem's complexities and nuances.

4.4 Scenarios

This section details each development phase of the recommendation system, addressing challenges, proposed solutions, and potential future improvements.

- Data Collection: The initial crucial step in developing the recommendation system involves collecting data from various sources like browsing history, user reviews, and demographic information. Ensuring data quality is vital for the system's efficacy, with privacy and ethical considerations paramount in protecting user personal information.
- Data Preparation: Collected data is pre-processed and organised into a suitable analysis format, including data cleaning, removing irrelevant information, and standardising data formats. Cleaning involves correcting typing errors, standardising terms, and eliminating duplicates or inconsistencies. Data transformation might include converting categorical data to numerical or normalising values across different scales. Post-processing data quality significantly impacts the recommendation system's accuracy and effectiveness.
- Machine Learning Model Construction: With collected and pre-processed data, the machine learning model is built, employing collaborative filtering for the recommendation system presented here. Collaborative filtering, a machine learning technique, uses other users' ratings with similar preferences to provide personalised recommendations [21].
- Model Training and Testing: The collaborative filtering model is trained using training and test data sets. The training set adjusts the model's parameters, while the test

set evaluates the system's accuracy and effectiveness. Various cross-validation methods like k-fold or repeated validation are used for data splitting. Adjusting model hyperparameters, like learning rate and regularisation, is crucial to avoid overfitting and enhance recommendation accuracy.

- System Effectiveness Evaluation: After training, the recommendation system's effectiveness is assessed using the test set. Metrics like mean squared error, precision, recall, and F1 score evaluate system accuracy and effectiveness. Additionally, recommendation diversity and user satisfaction are crucial considerations.

- Recommendation System Implementation and Update: With a trained and evaluated model, the recommendation system is implemented in a production environment. Regular monitoring and updating ensure continued relevance and usefulness as user interests and preferences evolve. Updates might include model data refreshing, hyperparameter adjustments, and new machine learning features or techniques incorporation.

- Hybrid Approach and System Expansion: Improving the system further may involve a hybrid approach combining collaborative filtering with other machine learning techniques, such as content-based filtering or deep learning. Combining these techniques could lead to a more robust and precise system, capable of handling diverse data types and user preferences.

Table 1 illustrates a prospective correlation between various conditions and symptoms and the potential medical specialties indicated. The data in this table represent the synchronisation between reported symptoms and the suitability of the medical specialty, expressed in percentage terms, symbolising the degree of correlation between the condition/symptom and the indicated specialty. The goal is to offer a simplified yet elucidative view of potential patient direction based on their respective conditions or symptoms. Table 2 is a compendium of pertinent information about various conditions and symptoms and their correlations with suitable medical specialties. Each table line is dedicated to a unique patient, identified by a random ID number for confidentiality. For each patient, the present conditions or symptoms are listed, and a correlated medical specialty is proposed based on these data. The percentage of indication reflects the compatibility between conditions/symptoms and the suggested medical specialty, providing an indicator of accuracy probability in the indication. For instance, an 80% indication percentage in Gastroenterology for a patient with abdominal pain and fever suggests a high correlation between reported symptoms and the indicated specialty. The alternating colours in the lines aim for a clear visual distinction between different data sets, facilitating quick analysis and interpretation of the presented data. This compendium not only eases understanding the correlation between various conditions and symptoms and possible medical specialties but also serves as a quick reference for healthcare professionals in determining appropriate patient referrals, thereby optimising response time and diagnostic precision. Thus, the presented recommendation system demonstrates the potential of machine learning techniques, like collaborative filtering, to enhance user experience across sectors. Through a systematic approach involving data collection, preparation, model construction, and evaluation, an efficient and accurate recommendation system was developed. Evaluating the system's efficacy is crucial to ensure the recommendations provided are relevant and useful to users, and considering hybrid approaches and system expansion could lead to further improvements in accuracy and user satisfaction.

Table 1: Patients and Their Conditions/Symptoms.

Patient ID	Conditions/Symptoms
9823612	Abdominal pain, Fever
4537192	Coughing blood, Weight loss
3617814	Joint pains, Swelling
1273619	Headache, Blurred vision
2918741	Chest pain, Shortness of breath
5762319	Hearing problems, Tinnitus
1287324	Depression, Anxiety
3127659	Blurred vision, Red eyes
7812365	Excessive thirst, Weight loss
1239672	Fracture, Bone pain
5921347	Urinary problems, Pelvic pain
4217365	Allergies, Skin rash

Table 2: Indicated Specialty and Percentage of Indication.

Indicated Specialty	% of Indication
Gastroenterology	80%
Pulmonology	75%
Rheumatology	90%
Neurology	85%
Cardiology	95%
Otolaryngology	80%
Psychiatry	70%
Ophthalmology	85%
Endocrinology	80%
Orthopedics	90%
Urology	75%
Dermatology	70%

4.5 Model Execution

This section presents the implementation process of the model based on clinical examination data and patient records, including family health history. The AI analyses this data to indicate the most appropriate medical specialty for patient referral. Data collection occurs in two phases. First, patient clinical examinations and records are acquired from medical histories. Next, if available, related family members' clinical examinations are obtained. Adhering to ethical and privacy guidelines in data collection is crucial to ensure patient and family protection. After data collection, a pre-processing step organises and structures the information according to the computational model's requirements. This includes data quality checks, duplicate removal, missing value handling, and inconsistent information treatment.

An exploratory analysis then examines the data for patterns and correlations among variables, aiding attribute selection for model training. This analysis also identifies potential data adjustments needed. Data collection for this research spanned six months from July to December 2022, with the sample progressively expanding to include more patients and examinations. This data analysis was key to training and validating the AI model and assessing its accuracy in identifying the right medical specialty for a patient. During July 2022, the initial month, the sample comprised 89 patients and 192 exams, prescriptions, and medical histories. These initial data were instrumental in the model's early development phase, used to adjust initial parameters and test data pre-processing and cleaning techniques. A robust data cleaning process was implemented to ensure data quality and reliability.

In August 2022, the sample expanded to 302 exams from 147 patients, allowing more effective model training and emerging trend identification. This phase also refined data pre-processing and cleaning techniques and adjusted model parameters to enhance accuracy and performance. From September to December 2022, the sample grew to include 546 exams from 274 patients, 663 exams from 331 patients, 861 exams from 482 patients, and finally, 1189 exams from 712 patients. As the data sample increased, the model was trained and validated with a more representative dataset, assessing its robustness against a broader range of data and continuously improving its accuracy and performance. Data quality and reliability remained paramount throughout this process. All data underwent rigorous cleaning and quality control processes to ensure suitability for analysis. All relevant ethical guidelines were followed, with necessary measures taken to protect patient data privacy and confidentiality.

This research phase demonstrated the viability and effectiveness of the proposed AI model in identifying the appropriate medical specialty for a patient based on their medical data. The results indicate the model's ability to successfully process and analyse large volumes of medical data and provide accurate and useful medical specialty recommendations. Data collection and analysis were fundamental steps in the research, allowing the training and validation of the AI model, identification of emerging trends and patterns, assessment of the model's robustness, and ultimately, demonstrating its capability to identify the right medical specialty for a patient.

With the data properly prepared, the computational model's training process begins. The dataset is split into training and validation sets, ensuring proper evaluation of the model's performance. The model is trained using supervised learning algorithms, where the AI learns to correlate input attributes (clinical exams and records) with the expected outcome (appropriate medical specialty). During AI training, various hyperparameters and learning strategies are tested to achieve optimal model performance. Cross-validation techniques help select ideal parameters, avoiding issues like overfitting and underfitting. After training, the model is validated using the validation dataset, not used during training. This allows a fair assessment of the model's performance and generalisation ability and identifies potential improvements.

Post-implementation, continuous performance evaluation of the model is crucial. Performance indicators such as accuracy, recall, and precision measure the quality of the model's indications. Additionally, an analysis of cases where the model erred identifies possible improvements and adjustments. Continuous performance monitoring ensures the quality and reliability of medical indications provided to patients. If performance declines or inconsistencies in indications are identified, the model must be updated and adjusted as needed. Medicine is constantly evolving, and new knowledge and discoveries can directly impact medical specialty indications. Therefore, keeping the model updated and aligned with the latest evidence and medical practices is essential. Maintaining the model involves monitoring new research, publications, and medical guidelines, and integrating new patient and family data. Additionally, periodically reevaluating and revalidating the model ensures it continues to perform satisfactorily and provide appropriate medical indications.

5 Results and discussion

The proposed computational model's results, implications, and challenges encountered in its development and implementation are as follows: the model's training and validation process yielded notable performance, with an average precision of 62%, recall of 46%, and F1-Score of 53%. These suggest the model's capability to accurately recommend medical specialties based on data analysis of clinical exams, patient records, and family health history. The model's versatility is evident in considering cases where general physicians can conclude treatment without referring to a specialist. This reflects real medical situations, demonstrating the model's applicability. The significant progress in AI applied to medicine validates the development of systems that significantly assist healthcare professionals in patient referrals. This capability for informed and accurate referral decisions can lead to better time management for doctors, optimised treatment processes for patients, and ultimately, more efficient and effective healthcare service delivery. Error analysis revealed most mistakes occurred in cases with symptom overlap or similar medical conditions across specialties, highlighting the need for model refinement to increase precision and address complex cases.

Exploratory data analysis identified key input variables impacting medical specialty recommendations, including family medical history, specific clinical test results, and patient age. These input variables emphasise the importance of collecting detailed patient and family information to improve medical recommendations' quality. During development and implementation, challenges included data availability and quality. Incomplete or outdated medical records affected model performance, and privacy and consent issues sometimes hindered family data collection. Addressing these limitations requires efficient strategies for precise and updated data integration.

Medical condition diversity and complexity posed challenges, especially for conditions with similar symptoms. Improving the model's ability to handle medical complexity, such as incorporating specialised medical knowledge, is crucial. Model updating and maintenance are ongoing challenges in the ever-evolving medical field. Keeping the model updated with the latest medical evidence and practices is vital to ensure its continued accuracy and relevance. Future perspectives include enhancing the model with new data like genetic information and biomarkers, adapting the model to other healthcare contexts, and integrating it with clinical decision support systems. Additionally, evaluating the model's impact on patient care and clinical outcomes can provide further evidence of its efficacy and relevance, contributing to its continuous validation and improvement.

5.1 Threats to Validity

The validity of results from the proposed computational model may be affected by factors like the quality and representativity of training and validation data, biases in training data, choice of learning algorithms and data pre-processing techniques, and the ability to generalise results to other patients and contexts. This section details each validity threat and suggests ways to minimise them, enhancing result reliability.

Data quality and representativity are crucial for valid results. If data doesn't adequately represent the target population, the model may struggle to generalise to other patients and contexts. For example, if data is primarily from a specific demographic or age group, the model might not accurately indicate specialties for different groups. Biases in training data, like under-representation of certain demographics or medical conditions, can lead to poor model performance in certain cases. To minimise this, it's essential to collect more representative data and ensure training data covers a wide range of demographics and medical conditions. Data balancing techniques like oversampling and undersampling can address class imbalance issues. Confirmation bias, the unconscious tendency to select input variables that confirm pre-existing expectations, can lead to a model more aligned with initial assumptions than actual data. To reduce this bias, a systematic and objective approach in feature selection is crucial, using statistical methods and machine learning algorithms to identify relevant input variables.

Overfitting or underfitting in the model can threaten result validity. Overfitting, where the model is overly complex and fits too closely to training data, loses generalisation ability. Underfitting, where the model is too simple, fails to capture data complexity. To address these issues, cross-validation techniques and careful hyperparameter selection are key. Regularisation techniques like L1 and L2 can control model complexity, and ensemble methods like bagging and boosting can improve generalisation and robustness. Methodological limitations, like choice of learning algorithms and data pre-processing techniques, can impact result validity. For example, supervised learning algorithms require labelled data and may not suit problems with limited input-output relationship information. Data pre-processing techniques can introduce errors or distortions, affecting model performance.

To tackle these limitations, consider different algorithms and pre-processing techniques, evaluating their impact on model performance. Unsupervised, semi-supervised, or rule-based learning algorithms can be alternatives when labeled data is scarce. External validity, the ability to generalise results to other contexts and populations, may be limited by medical condition variability, healthcare system differences, and patient and family data availability and quality. To enhance external validity and clinical applicability, validate the model with external data from different contexts, including multicentric studies involving various healthcare systems and populations. Adapting the model to regional and cultural specificities is also crucial. This might involve customising model parameters, including context-specific input variables, or developing specific models for different populations and contexts.

Addressing these validity threats is essential for improving the applicability and reliability of the computational model, allowing its implementation in real clinical contexts and benefiting patients and healthcare professionals in making informed and effective decisions.

5.1.1 Validation

The model's validation involved various techniques to ensure reliability and generalisation of results, including:

- Cross-validation: Used during training and evaluation to divide data into training and testing sets, this technique checks model performance on different data subsets and reduces overfitting risk [10].
- Testing with external data: To assess external validity, the model's performance was tested on external datasets from diverse sources and contexts, verifying its generalisation capability to other patients and situations [29].
- Sensitivity and specificity analysis: Along with precision, recall, and F1 measures, sensitivity and specificity analysis checked the model's effectiveness in correctly identifying medical specialties and excluding incorrect ones, respectively [18].

Measures implemented to mitigate validity threats included:

- Collecting representative data: Data from patients and related family members were obtained to ensure the model's applicability across a wide range of cases [31].
- Evaluating learning algorithms and pre-processing techniques: Various supervised learning algorithms were tested, and appropriate data pre-processing techniques were applied to minimise errors and distortions [11].
- External validity and model adaptation: Validation with external data and consideration of regional and cultural specificities enhanced the model's generalisation to other contexts and populations [24].

Validation results confirmed the computational model's satisfactory performance, showing consistent accuracy, recall, F1 measure, sensitivity, and specificity across different datasets and contexts. This suggests the model can provide suitable, generalisable medical specialty indications for patients with diverse characteristics and medical conditions [20]. The proposed computational model's validation demonstrated its generalisability and reliability. The validation process, including various techniques and mitigating validity threats, improved the model's applicability and robustness. Based on validation results, the model has potential for real clinical context implementation, benefiting patients and healthcare professionals in informed, effective decision-making [25]. Successful clinical implementation requires integrating the model with clinical decision support systems and adapting it to specific context and population needs. Considering feedback from healthcare professionals and patients is crucial for identifying improvement areas and ensuring the model's ongoing evolution and relevance. With proper validation, the proposed computational model can become a valuable tool for patient referral to medical specialties, enhancing medical care quality and efficiency, and positively impacting patient lives and healthcare practice. However, ongoing research and development are essential to further refine the model and expand its applicability, ensuring sustained, widespread benefits.

6 CONCLUSIONS

The study of Artificial Intelligence (AI) in medicine is a promising field with the potential to significantly improve healthcare quality and efficiency. This research explored AI's ability to analyse medical data and suggest appropriate medical specialties for patients, based on patterns and correlations in the data. The research provided significant insights into AI's contribution to medicine, highlighting its potential not just for interpretation but also for predicting medical conditions from health data patterns. The results validate that properly trained and validated AI systems can be valuable tools for healthcare professionals, offering relevant insights to influence clinical decisions and facilitate more accurate and efficient referrals. This study extensively explored various algorithms and techniques to develop a robust and precise model. Results showed an average precision of 62%, recall of 46%, and an F1 measure of 53%, indicating the model's capability to provide suitable medical specialty indications with acceptable accuracy.

Given the vast amount and diversity of medical data analyzed, these results are promising, showing the potential to assist general practitioners in decision-making for specialist referrals, thus optimising the diagnostic and treatment process. The model also demonstrated significant accuracy in cases where general practitioners could conclude treatment, potentially easing the burden on specialists and improving overall healthcare efficiency. However, it's crucial to note that AI doesn't replace the need for qualified medical professionals; instead, it serves as a complementary tool that can enhance medical service accuracy and efficiency. Human interpretation of AI-provided results remains essential for ensuring diagnostic accuracy and treatment appropriateness.

This work also underscores the importance of ongoing investigations and developments in AI for medicine. There's a vast unexplored field of possibilities and improvements, including optimising existing algorithms and developing new approaches and techniques for more accurate and reliable results. Additionally, while clean and approved data proved valuable for the final results, the challenge of data quality highlighted the importance of data processing and cleaning in applying AI to medicine. A deeper analysis of raw data and the application of more sophisticated pre-processing methods could improve AI model accuracy. While this work's contributions to the field are significant, future studies with broader and more diverse datasets, possibly integrating additional variables that may influence medical specialty indications, are recommended to enhance the precision and applicability of the developed models.

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