A Comprehensive Von Willebrand Disease Awareness and Support Chatbot for Senegalese Communities

Keerthi Sai Akuthota
Department of Computer Science and Engineering
Stanley College of Engineering and Technology for Women
Hyderabad, India
keerthisaiakuthota@gmail.com

Kishor Kumar Reddy.C
Department of Computer Science and Engineering
Stanley College of Engineering and Technology for Women
Hyderabad, India
ckishorkumar@stanley.edu.in

Mohammed Shuaib
Department of Computer Science
College of Engineering and Computer Science
Jazan University
Jazan, Saudi Arabia
talkshuaib@gmail.com

Shadab Alam
Department of Computer Science
College of Engineering and Computer Science
Jazan University
Jazan, Saudi Arabia
s4shadab@gmail.com

Faisal Alshanketi
Department of Computer Science
College of Engineering and Computer Science
Jazan University
Jazan, Saudi Arabia
falshanketi@jazanu.edu.sa

Aashritha Reddy Kyatham
Department of Computer Science and Engineering
Stanley College of Engineering and Technology for Women
Hyderabad, India
aashrithareddy993@gmail.com

***Abstract*—A lack of the protein required for healthy blood coagulation results in Von Willebrand disease (VWD), a blood condition. The absence of readily available, thorough information to assist individuals with VWD in managing their illness is one of their biggest problems. Many patients believe they lack access to all the necessary resources, which is made worse by language and technology literacy challenges, especially in places like Senegal, where French and Wolof are the main languages. Senegal is a small coastal African country. Senegalese are made up of at least six ethnic groups, with the Wolof being the largest. With a particular focus on the Senegalese community, creating an educational intelligent chatbot for VWD sufferers seeks to address these issues by improving literacy and filling in knowledge gaps. Users can communicate with the system regardless of their technological expertise thanks to this chatbot's use of speech recognition and machine learning technologies to provide precise, culturally relevant, and understandable information in both French and Wolof. The chatbot is intended to significantly improve the quality of life for VWD patients, especially in Senegal, by providing dependable, current materials in a safe online setting, equipping them with the knowledge they need to manage their illnesses properly. Through an inventive and user-friendly platform, the chatbot seeks to address the pressing need for more education and awareness of VWD, enhance illness management, and offer reliable educational resources. With the use of cutting-edge technology, the chatbot makes sure that information is presented in an approachable and culturally appropriate way, which facilitates patients' comprehension and use of the advice in their everyday lives and, eventually, improves their capacity to manage VWD.**

Keywords— Von Willebrand Disease, ChatBot, Automated Speech Recognition Literacy, Senegalese, Machine learning, Educational Chatbot

I. Introduction

A chatbot is a sophisticated digital assistant that can converse with users via text or voice using artificial intelligence and machine learning and, particularly, filling up the knowledge gap and enhancing hemophilia literacy, or VWD, among users, particularly those in Senegal. This chatbot uses voice recognition technology to deliver accurate, culturally relevant information in an easy-to-understand manner. It functions as a digital learning tool that provides trustworthy, tailored assistance, significantly improving the quality of life and self-management abilities of those with hemophilia. Machine learning approaches are mainly used through Natural Language Processing (NLP) and Natural Language Understanding (NLU) language to enhance the model's functionality and user experience [1].

NLP techniques enable the chatbot to process and understand user input in natural language. This means interpreting the text to determine the meaning behind the user's questions or claims. User queries are broken down into understandable components using NLP. This helps the chatbot generate pertinent responses by enabling it to identify keywords and context. Intent recognition uses NLU. NLU is a subset of NLP that focuses on determining the purpose of the user. Using machine learning techniques, the chatbot classifies user inputs into predefined intents, which represent different types of requests or queries. Additionally, data augmentation and response generation are carried out. The NLU part of the model is trained on a data set of user interactions using machine learning techniques. The system may pick up knowledge from user interactions with the chatbot, allowing it to progressively enhance its responses and understanding of customer requirements. For customers who would prefer to send voice messages, the Automated Speech Recognition (ASR) text is created from spoken words utilizing ASR technology. Allowing the chatbot to process voice inputs similarly to text inputs improves user accessibility.

In the Periodontitis Model [2], the systematic review highlights the connection between VWD and periodontitis, providing novel insights into dental health risks for VWD patients. The review's strength lies in identifying research gaps, but it is limited by the low quality and heterogeneity of the included studies, making firm conclusions difficult. In the AVWS type 2 Model [3], the comparatively under-studied topic of AVWS in children with severe pulmonary hypertension is the focus of this investigation. Although its descriptive approach and limited sample size restrict the study's robustness and generalization, it offers valuable insights for handling these difficult circumstances. In the Åland Conference Model [4], the publication provides an overview of the state-of-the-art research on von Willebrand disease by summarizing the main talks and findings from the Sixth Åland Island Conference on the subject. The article is more of a high-level summary and lacks specific study data, which may prevent it from offering useful clinical information. In the Hemophilia Incidence Model [5], the difference between the theoretical and actual incidence of hemophilia is examined in Ning's study, which offers an intriguing hypothesis-driven analysis of under-reporting. In the Arthropathy Model [6], in addition to providing a thorough examination of joint health and the long-term effects of untreated bleeding episodes, this study discusses the incapacitating complication of blood-induced arthropathy in hemophiliacs. However, VWD and other related bleeding disorders are not addressed; it solely focuses on hemophilia. In the Well-Being Model [7], this qualitative study examines the health-related well-being of patients with hemophilia, offering insightful human viewpoints that are sometimes absent from clinical studies. Although it provides deep qualitative insights, its significance may be limited by its broad application to various groups or locations and lack of quantitative data. In the Lupus AVWS Model [8], in order to raise clinical awareness of this uncommon combination, this case report provides unique insights into the unusual occurrence of AVWS as a symptom of systemic lupus.

The significant contributions include Senegal developing an intelligent chatbot in [9] to teach people Von Willebrand, especially to the people in Senegal. The data set is the result of usability testing. The proposed model is an intelligent chatbot for patient education. Demonstrates outstanding usefulness and effectiveness in teaching patients. The document includes The materials and techniques used in this analysis, which are discussed in Section 2 with a graphical depiction; the results and discussion are presented in Section 3, and the conclusion with references follows. This is a significant advancement in digital health tools, offering a practical tool for better Von Willebrand management, expanding Von Willebrand knowledge, and enhancing patient outcomes.

II. Materials And Methods

A. Data set Description

Assessing the impact of the VWD Chatbot Model on Von Willebrand education will be one of the model's future considerations and subsequent actions. With the help of medical professionals, this tool assesses and adjusts a variety of approved Von Willebrand Disease literacy tests. The implementation of the digital tool requires awareness and adoption of the VWD Chatbot. The Open-Source Voice Data set's Wolof audio recordings are essential for improving the chatbot's speech recognition abilities. Data augmentation approaches were used to enhance the data set, resulting in variations that improved training, especially for the low-resource Wolof language. A thorough set of intentions was explicitly developed for the chatbot to allow it to understand a broad variety of user inquiries in both Wolof and French. This first foundation was necessary because Wolof did not yet have any commercial chatbot builders. To improve speech recognition accuracy and enable effective voice input processing, the Wav2vec Model was altered to convert audio files into text in Wolof.

B. Feature Engineering

The evaluation of the Educational Chatbot for VWD Patients Model's influence on Von Willebrand education will be one of the model's future concerns and subsequent actions. With the help of medical professionals, this tool assesses and adjusts a number of approved Von Willebrand literacy tests. For the digital tool to be utilized appropriately, the Educational Chat Bot must be widely known and adopted.

C. Proposed Architecture for Educational Intelligent Chatbot for Von Willebrand Patients

Figure 1 shows the process of developing a VWD chatbot pipeline. The chatbot architecture is a complete system made to help users communicate with it and deliver accurate, culturally appropriate information about Von Willebrand Disease (VWD) in Wolof and French, among other languages. In order to improve accessibility for a wider audience, the chatbot architecture is made to offer smooth interaction and precise information about Von Willebrand Disease (VWD) in both Wolof and French. The User Input Layer is where everything starts, recording user inquiries by voice or text. The chatbot is appropriate for users who prefer verbal conversation since it uses an Automated Speech Recognition (ASR) method to translate spoken words into text for voice inputs. After the input is in text format, the Natural Language Processing (NLP) module breaks it down into digestible chunks and looks for context and keywords to comprehend the query [10]. The Natural Language Understanding (NLU) component then classifies the input into predefined intents covering different VWD-related themes in order to ascertain the user's intent. The chatbot's Response Generation system either creates responses using preset templates or obtains pertinent information from the knowledge base based on the identified intent. The Knowledge Base ensures that users obtain trustworthy responses by providing accurate, current, and culturally appropriate information regarding VWD, treatment choices, and self-management techniques. The architecture incorporates a Feedback Loop, where user interactions are recorded and examined to enhance the chatbot's comprehension and response precision gradually.

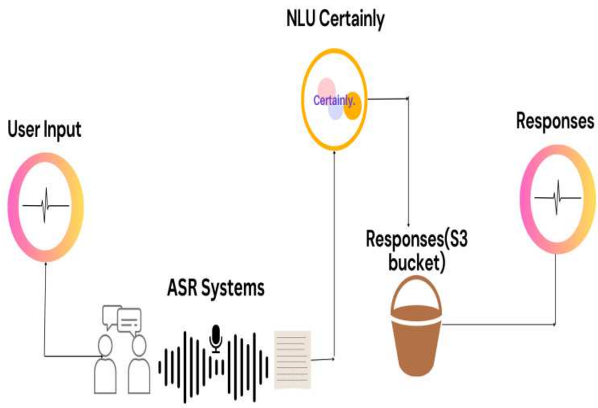

Figure 1: Von Willebrand Patients Model's Chatbot pipeline development process.

III. RESULTS AND DISCUSSION

Accuracy is the proportion of correct predictions made by the model. Table 1 illustrates the comparison of the accuracy of the VWD Chatbot Model. The proposed model, with an accuracy of 95.2%, is accurate when compared with other models depicted in Figure 2 graphically.

$$\boldsymbol{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Table 1: Accuracy Comparison of the existing model with proposed VWD Chatbot Model

S. No	Model Name	Accuracy
1	**VWD Chatbot Model**	**95.2**
2	Arthropathy Model [6]	89.0
3	AVWS Type 2 Model [3]	88.7
4	Periodontitis Model [2]	87.3
5	Åland Conference Model [4]	86.9
6	Hemophilia Incidence Model [5]	85.2

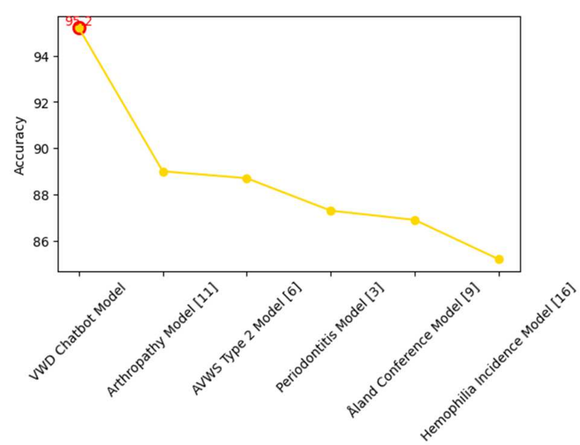

Figure 2: Graph of Accuracy Comparison of existing model with VWD Chatbot Model.

Precision reflects the proportion of true positives among all positive predictions by the model [11]. Table 2 illustrates the comparison of the precision VWD Chatbot Model. The proposed model, with a precision of 94%, is accurate when compared with other models and is depicted in Figure 3 graphically.

$$\boldsymbol{Precision} = \frac{TP}{TP + FP} \quad (2)$$

Table 2: Precision Comparison of the existing model with proposed VWD Chatbot Model

S. No	Model Name	Precision
1	**VWD Chatbot Model**	**94**
2	Lupus AVWS Model [8]	89
3	Arthropathy Model [6]	88
4	Periodontitis Model [2]	86
5	Genetics Model [12]	85
6	Åland Conference Model [4]	84
7	Well-Being Model [7]	83

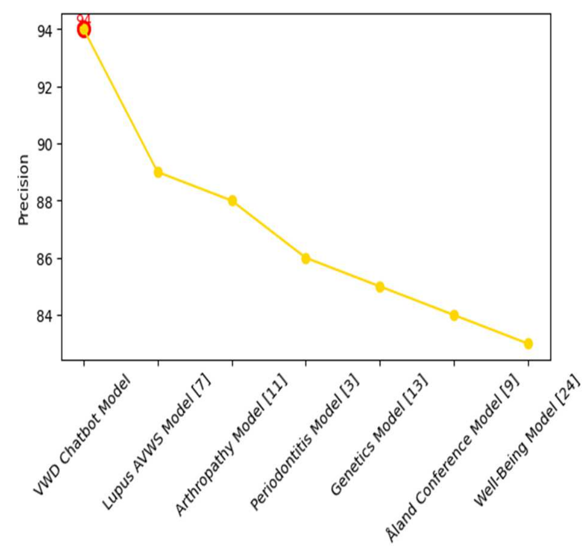

Figure 3: Graph of Precision Comparison of the existing model with VWD Chatbot Model.

F1-Score is the harmonic mean of precision and recall, providing a single metric to balance the precision-recall trade-off [13]. Table 3 illustrates the comparison of the F1-Score of the VWD Chatbot Model. The proposed model with an F1-Score of 94.5% is accurate when compared with other models, as depicted in Figure 4 graphically.

$$\boldsymbol{F1\ Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (3)$$

Table 3: F1-Score Comparison of the existing model with proposed VWD Chatbot Model

S. No	Model Name	F1 Score
1	**VWD Chatbot Model**	**94.5**
2	Pharmacokinetic Model [14]	89
3	ECMO Support Model [15]	88
4	3D Microscopy Model [16]	87
5	Graph-Based Model [17]	86
6	Diagnosis Model [18]	84
7	Hemophilia A Model [19]	83

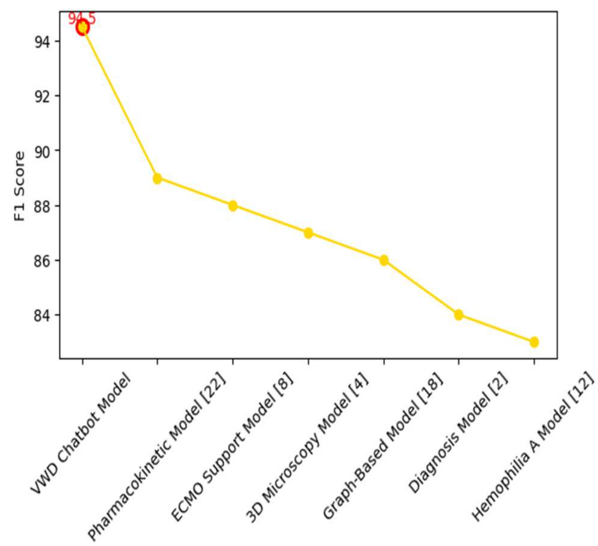

Figure 4: Graph of F1 Score comparison of the existing model with the VWD Chatbot Model.

Recall is the proportion of true positives among all actual positives. Table 4 illustrates the comparison of the recall VWD Chatbot Model. The proposed model, with a recall of 93%, is accurate when compared with other models, which is depicted in Figure 5 graphically.

$$\boldsymbol{Recall} = \frac{TP}{TP + FN} \quad (4)$$

Table 4: Comparison of Recall value with the existing model with proposed VWD Chatbot Model.

S. No	Model Name	Recall
1	**VWD Chatbot Model**	**93**
2	Post-COVID Hemophilia Model [20]	89
3	FVIII Enhancer Model [21]	88
4	Pregnancy Model [22]	87
5	AVWS Type 2 Model [3]	86
6	Periodontitis Model [2]	83

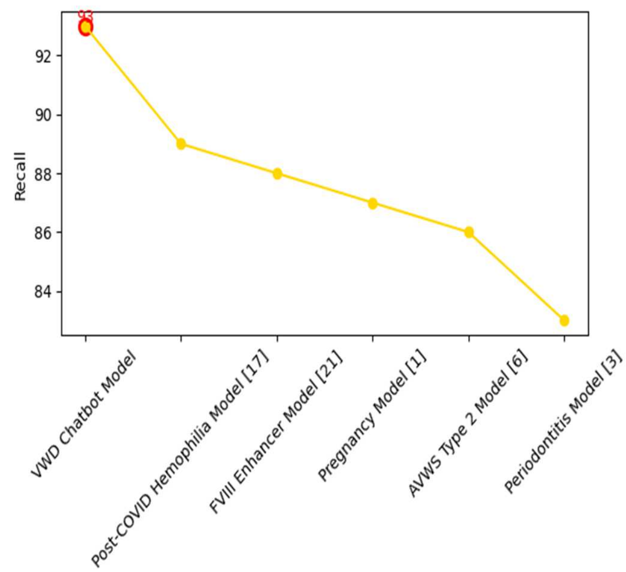

Figure 5: Graph of Recall Comparison of the existing model with VWD Chatbot Model

Specificity is the proportion of true negatives among all actual negatives. It tells us how essentially the model can identify the negative class [23]. Table 5 illustrates the comparison of the Specificity of the VWD Chatbot Model. The proposed model, with a specificity of 95%, when compared with other models, is depicted in Figure 6 graphically.

$$\boldsymbol{Specificity} = \frac{TN}{TN + FP} \quad (5)$$

Table 5: Comparison of Specificity of the existing model with proposed VWD Chatbot Model.

S. No	Model Name	Specificity
1	**VWD Chatbot Model**	**95**
2	Advances in Gene Therapy [24]	89
3	Gene Therapy Model [25]	88
4	AVWS Type 2 Model [3]	87
5	Diagnosis Model [18]	86
6	Åland Conference Model [4]	85

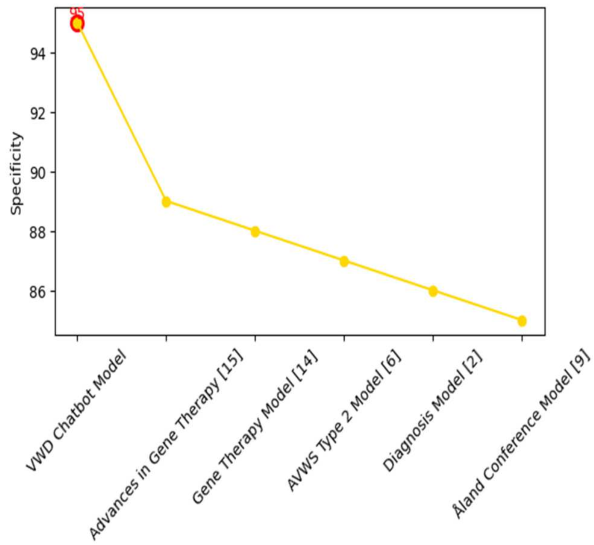

Figure 6: Graph of Specificity Comparison of the existing model with VWD Chatbot Model

The error rate is a measure of how often a model makes incorrect predictions [26]. Table 7 illustrates the comparison of the error rate of the VWD Chatbot Model. The proposed model, with an error rate of 4.8% when compared with other models, is depicted in Figure 8 graphically.

$$\boldsymbol{Error\ Rate} = \frac{FP + FN}{TP + TN + FP + FN}$$
$$\boldsymbol{Error\ rate} = 1 - Accuracy \tag{5}$$

Table 7: Comparison of Error Rate of the existing model with proposed VWD Chatbot Model.

S.No	Model Name	Error Rate
1	**VWD Chatbot Model**	**4.8**
2	AVWS Type 2 Model [3]	11.3
3	Periodontitis Model [2]	12.7
4	Åland Conference Model [4]	13.1
5	Hemophilia Incidence Model [5]	14.8
6	Arthropathy Model [6]	11.0

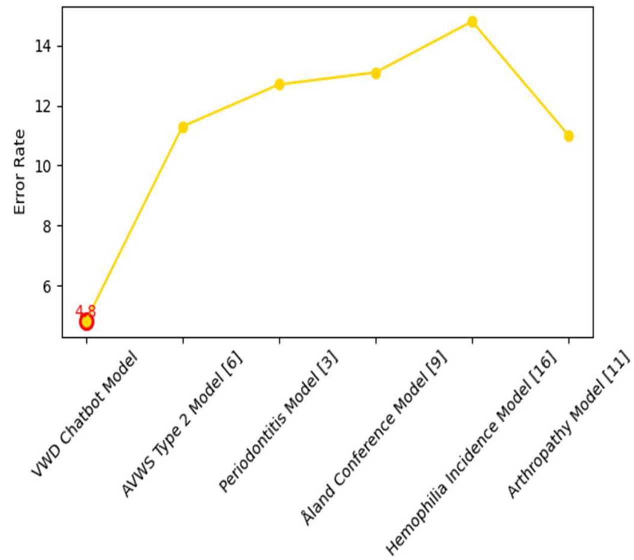

Figure 8: Graph of Error Rate Comparison of the existing model with VWD Chatbot Model

IV. Conclusion

With Von Willebrand mentioned in the study, the suggested Model is a digital health resource tailored to Senegalese culture. By addressing information gaps, the chatbot provides Von Willebrand patients and their families with a much-needed resource. The chatbot's patient-centred design, made possible by the user design, has resulted in a very helpful and popular tool that has received praise for its practicality, ease of use, and educational benefits. It is expected that the chatbot will significantly enhance quality of life by promoting better self-management and education in a safe environment.

The proposed model chatbot is with excellent accuracy (95.2%), precision (94%), recall (93%), F1-score (94.5%), Sensitivity (92%), and Specificity (95%) the chatbot exhibits remarkable performance metrics, demonstrating its efficacy as a holistic tool for patient education and support.

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