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ENHANCING PATIENT SAFETY IN HEALTHCARE THROUGH PUBLIC OPINIONS USING DEEP LEARNING

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Article Info

Abstract

This research seeks to analyze the use of sentiment analysis (SA) to enhance patient safety and healthcare service delivery by evaluating patients' perceptions of social media and healthcare websites. It contrasts the results of the experiments with support vector machines (SVM), logistic regression (LR), naive bayes (NB), and a fine-tuned BERT model for SA. The labeled patient review dataset used in this study was collected from social media websites such as Facebook, Twitter, and Marham.pk. Text cleaning, such as text normalization, TF-IDF vectorization, and BERT tokenization, were applied to the dataset to make it fit for analysis. The findings show that the fine-tuned BERT model provided a better prediction result than the previous models with 97% accuracy owing to the enhanced contextual meaning representation and sentiment sensitivity. Conversely, classical models displayed relatively good performance with mean accuracy scores but poor ability to deal with intricate language. The study identifies the possibility of combining new SA methods with service quality models to support fact-based decision-making in healthcare. However, the model has some limitations that as high computational complexity and low interpretability compared with the previous ones. Future work is planned to expand the study of domain-specific transformers, increase computational efficiency, and introduce the concept of explainability into real-life applications of this type of model.

Keywords:

Machine Learning, SA, Deep Learning, BERT, Patient Safety.

INTRODUCTION

Patient safety is a critical aspect of healthcare quality, focusing on minimizing risks, errors, and harm to patients during the provision of medical services. Inadequate patient safety measures can lead to adverse events, medical errors, and a decline in healthcare service quality. The rise of digital platforms, particularly social media, has provided a new avenue for collecting and analyzing patient feedback. Public opinions expressed through online reviews, forums, and social media platforms serve as valuable sources of insight into hospital service quality and patient satisfaction. Data mining (DM) techniques have become increasingly popular in healthcare for extracting meaningful patterns and insights from vast amounts of data [1]. By analyzing structured and unstructured patient feedback, data mining helps healthcare providers understand common issues, improve service quality, and enhance patient safety. Traditional data mining techniques, such as SVM, NB, and LR, have been widely used for sentiment analysis in healthcare applications [2]. However, deep learning models, particularly transformer-based architectures like BERT (Bidirectional Encoder Representations from Transformers), have shown superior performance in sentiment classification tasks. SA, also known as opinion mining (OM), is a natural language processing (NLP) technique used to determine the sentiment behind textual data. In the healthcare domain, SA plays a crucial role in understanding patient experiences, identifying dissatisfaction trends, and addressing critical safety problems. Previous studies have leveraged machine learning models to classify sentiments into positive, negative, and neutral categories, enabling healthcare policymakers to make data-driven decisions. Diverse applications applied in sentiment classification in NLP is an essential tool as discussed by authors in [3]. This helps analyze customer feedback, tracks social media trends, and brings down a bucket full of valuable insights. SA is very important in Healthcare to see the patient's experiences, know concerns, and better services in healthcare [4]. The sentiments of patients expressed in online reviews and social media can help healthcare providers to understand healthcare provider also can understand patients' experiences likes and expectations. It allows them to pinpoint weaknesses they can fix, deal with the same old complaints, and raise the bar as it pertains to safety, all together creating trust and building on the relationship between patients and providers. Relating sentiment analysis with well-established service quality frameworks like SERVQUAL enables healthcare organizations to create a holistic, data-based decision-making process, which prioritizes the areas of improvement and delivers more patient-centered care. Through the continuous combination of qualitative and quantitative feedback, providers can not only refine their service continuously but also serve patient needs and stay competitive in the ever-changing healthcare landscape [5]. By reading patient comments or reviews written on the internet or social media, healthcare providers can know how patients will experience, and what are the patients concerned about and expect. It allows them to pinpoint what they need to improve upon, and what's the most common complaint and helps patients develop trust and build a good relationship with the providers. Combined with existing service quality frameworks, SA provides a data-driven approach in decision-making that aids healthcare organizations in identifying the areas to enhance and overall provide more patient-centered care. Providers can continually improve their service to meet evolving patient needs as well as stay competitive in an ever-changing healthcare landscape through a combination of qualitative and quantitative feedback. The field of transformer models, especially BERT has come very far towards achieving this by providing more accurate and contextualized sentiment interpretation of the text. These models are great for learning contextual meaning and fine details of language, which makes them ideal for interpreting messy, real-world data such as patient feedback. Powered by their ability to process large volumes of text with high accuracy, sentiment analysis has transformed their way of helping healthcare providers understand patient sentiment, resulting in meaningful changes to the quality of service [6]. In this study, we compare traditional machine learning models for sentiment classification, namely SVM, LR and NB, with a Fine-Tuned BERT model applied to healthcare feedback. In the study, the performances of these models in terms of accuracy, precision, and recall are evaluated, and the best way of sentiment analysis in healthcare is identified. The results will provide valuable insights into how healthcare providers can precede based on the strengths and limitations of each model to determine the best technique appropriate to their requirements. The study will also show how BERT can solve the problems traditional models have in understanding the dynamics of patient feedback. Ultimately, the findings are intended to help hone sentiment analysis in healthcare, leading to better service quality and better patient safety.

RESEARCH OBJECTIVES

The main objectives of this research study are following:

- To develop a labeled dataset of patient feedback by manual annotators.
- To compare classical ML models with fine-tuned BERT for sentiment classification of patient feedback, and
- To provide actionable insights for healthcare service improvement.

SCOPE OF THE STUDY

A labeled dataset of patient reviews labeled as Negative, Neutral, and Positive, collected from social media platforms and online healthcare sites (Marham.pk), has been used for this study. So feedback given on the data is of a very wide range like how did doctor-patient interaction and how did the treatment work? The study analyzes these reviews to identify patterns of patient sentiment to identify improvements to and strengths in health care services. This data will be worked on with sentiment analysis to help healthcare providers learn more about patient satisfaction and make data-driven decisions to raise service quality. The findings will ultimately guide more patient-focused healthcare and outcomes will improve, patient safety will also be enhanced.

RESEARCH GAP

Analysis of patient feedback has been a challenge in current methods, especially within Malaysian hospitals. However, most of the existing studies do not adequately integrate advanced machine learning techniques with the established service quality models [7]. Therefore, the potential of online patient reviews to drive improvements in healthcare services has not yet been fully utilized. Such a research gap impedes healthcare providers' ability to utilize data from a patient's feedback to make informed, data-driven decisions. This gap could enable a better-informed effort to improve service quality and more effectively improve patient outcomes in the healthcare sector.

CONTRIBUTION OF THE RESEARCH

This research makes the following key contributions:

- Development of a new, labeled dataset focused specifically on patient feedback in Pakistan, expanding available resources for research in this area.
- Expansion of data sources to include a diverse range of platforms, encompassing Facebook, Twitter, and Marham.pk, providing a more comprehensive view of patient experiences.
- Development of an automated framework for real-time analysis of patient feedback, enabling proactive identification of potential issues and facilitating timely interventions to improve healthcare services.

REVIEW OF RELATED LITERATURE

This paper aims to give an insight into the ongoing research and achievements of sentiment analysis by revolving around the traditional machine learning approach and the novel developed transformers and BERTs. This takes a look at the drawbacks and advantages of these conventional models to find out how the more effective transformer models compare to them. The review also focuses on the exposure of the applicability of sentiment analysis in the context of the healthcare sector, in which the explanation of the sentiments has emerged as vital for enhancing the quality of healthcare services. Furthermore, it also explores how this sentiment analysis can be combined with other tested theories like SERVQUAL to enact a strong framework for enhancing healthcare experiences. Together, these methodologies allow for health care organizations to make effective, efficient decisions directly impacting patient care. From a broader perspective, this integration is useful in solving patients' issues, enhancing operational efficiency, and producing better care service delivery. The following literature focuses on the pros and cons of healthcare sentiment analysis as well as the difficulties that come from medical terms and the subjective character of words. It highlights problems that such imprecise and indirect feedback poses for understanding customers because people's feelings and experiences are so diverse and manifold. Furthermore, the presented review discusses how more sophisticated models such as transformers can tackle these issues due to their ability to make sensitive and accurate evaluations of sentiments. However, the study provides an understanding of areas that need work to achieve the maximum utilization of sentiment analysis in patient-centric, data-led decision-making. The study implies that it may be possible to make better use of patient feedback information, which may enhance the treatments, and services offered to patients. Finally, the review encourages more research and development of sentiment analysis for improved precision and general use in the medical field [6]. Although SA is particularly useful in m-Healthcare, it also poses peculiarities that call for certain standard approaches to work with medical language. This is because using the terms themselves the medical field is complex along with the many different ways that patients can describe their experiences without context-aware models it is impossible to comprehend the likelihood of positive and negative statements. Moreover, due to the variety of patients' experiences which vary from technical to emotional, sentiment classification requires a more sophisticated approach. Most of the existing approaches and tools provide limited capabilities for evaluating medical discussions and patient feedback. Hence, there is a need to use sophisticated approaches in the analysis of text that originates from healthcare contexts, for example, the Transformer models. Hence, by deploying the specific approaches to eliciting the sentiments required herein, then sentiment analysis can help in offering better insights into the decision-making process as well as the delivery of services across the healthcare domain. Healthcare is challenging for SA because all significant information is contained in medical terms and jargon. The interest shown by patients is affirmative but widely diverse, depending on the patient's conditions, nationality, and attitude. Differences such as these become problematic in the traditional analysis of the results as it is challenging to get a sense of the overall positive, negative, or even neutral tones embedded in the texts. The development of ever more sophisticated models, such as the transformer-based ones, may prove more applicable to the context of healthcare textual data. They can give a meaning relative to the particular context and interrogate the variation in patient representations better. These techniques aid in gathering a clear understanding of the experiences of the patients, promoting better and patient-engaged decisions within the healthcare systems [8]. To extract useful analytics from healthcare-related sources, two main challenges have to be met: the semantic interpretation of medical texts and the analysis of feedback from patients. Fluency and subjective human language also bring difficulties into the analysis of the sentiment, as the estimation is ambiguous. These complexities are most apparent in the healthcare field because feedback is typically laden with social and technical aspects. These model complexities are necessary to address these issues and provide a more accurate and contextually-aware computation. Thus, in cases where such problems are solved, sentiment analysis can reveal much about a patient's experience. This, in turn, enables health service deliverers to make decisions per patient needs and improve service delivery based on factual data [9]. Establishing technical features for sentiment analysis helps the researchers to respond to the variety of patient experiences more adequately. Selective methods may enhance listener-oriented approaches in interpreting various forms of expressions and medical terms in health information. Through these adaptations, healthcare providers are thus in a good position to extract analysis that goes hand in hand with service enhancement. It aids in defining certain aspects that require focus to potentially bring improvements to patient care. In turn, such efforts lead to an increase in patient protection, as well as to the enhancement of the given services' quality. All these innovations provide the basis for more individualized and evidence-based care informing the operations of the health system [10]. It becomes possible to understand the specifics of the primary consumers' feedback analysis since it is necessary to challenge the existing approaches to sentiment classification in the healthcare context. Advanced tools which are created specifically for the purpose enable analysts to get more precise results when analyzing various and often laconic forms of expression. These propound developments help healthcare systems recognize areas of potential need for more effective service delivery and patient care. Therefore, it is suggested that sentiment analysis if implemented and used correctly can produce useful information required for improving various decision-making steps. This results in effective patient safety interventions hence pulling up the quality of service delivery. Finally, these challenges' resolution leads to a more patient-centered and productive model of health care [11]. In the context of digital health and incorporating sentiment analysis within this area the review outlines possible difficulties and potential in the analysis of medical texts and the usage of subjective language. Further, it underlines the significance of receiving the progression of distinctive approaches to address these issues and increase the credibility of sentiment analysis. This potential of using patient feedback extracted from online reviews, sharing, and social media is also stressed as strength for assessing patient experience. From this kind of feedback, healthcare providers can identify patterns, trends, and or issues. It can help us to develop patient safety initiatives and provide critical decisions about service delivery. In the long run, this approach is likely to improve the general receive care by patient-centeredness.

Although SA is particularly useful in m-Healthcare, it also poses peculiarities that call for certain standard approaches to work with medical language. This is because using the terms themselves the medical field is complex along with the many different ways that patients can describe their experiences without context-aware models it is impossible to comprehend the likelihood of positive and negative statements. Moreover, due to the variety of patients' experiences which vary from technical to emotional, sentiment classification requires a more sophisticated approach. Most of the existing approaches and tools provide limited capabilities for evaluating medical discussions and patient feedback. Hence, there is a need to use sophisticated approaches in the analysis of text that originates from healthcare contexts, for example, the Transformer models. 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These techniques aid in gathering a clear understanding of the experiences of the patients, promoting better and patient-engaged decisions within the healthcare systems [12]. To extract useful analytics from healthcare-related sources, two main challenges have to be met: the semantic interpretation of medical texts and the analysis of feedback from patients. Fluency and subjective human language also bring difficulties into the analysis of the sentiment, as the estimation is ambiguous. These complexities are most apparent in the healthcare field because feedback is typically laden with social and technical aspects. To overcome such considerations, sophisticated models like transformers are more novel and accurate when melded into a tool. Thus, in cases where such problems are solved, sentiment analysis can reveal much about a patient's experience. This, in turn, enables health service deliverers to make decisions per patient needs and improve service delivery based on factual data [13]. Establishing technical features for sentiment analysis helps the researchers to respond to the variety of patient experiences more adequately. Selective methods may enhance listener-oriented approaches in interpreting various forms of expressions and medical terms in health information. Through these adaptations, healthcare providers are thus in a good position to extract analysis that goes hand in hand with service enhancement. It aids in defining certain aspects that require focus to potentially bring improvements to patient care. In turn, such efforts lead to an increase in patient protection, as well as to the enhancement of the given services' quality. All these innovations provide the basis for more individualized and evidence-based care informing the operations of the health system. It becomes possible to understand the specifics of the primary consumers' feedback analysis since it is necessary to challenge the existing approaches to sentiment classification in the healthcare context. Advanced tools which are created specifically for the purpose enable analysts to get more precise results when analyzing various and often laconic forms of expression. These propound developments help healthcare systems recognize areas of potential need for more effective service delivery and patient care. Therefore, it is suggested that sentiment analysis if implemented and used correctly can produce useful information required for improving various decision-making steps. This results in effective patient safety interventions hence pulling up the quality of service delivery. The management of these issues leads to improved patient care hence a system that fosters patient neurological and metabolic requirements [14]. 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This renders it possible for machine learning algorithms to analyze and summarize textual data by breaking words into relationships and with sentiment. Because the data is digitized the above algorithms are more accurate in their prediction of sentiment. However, while traditional approaches are helpful in what they do, they generally tend to fail to capture nuances of language. A considerable number of weakly marked, grey, or contextual semantically related words like sarcasm, irony, and context-dependent words do influence the effectiveness of sentiment classification. These difficulties illustrate the problems with conventional methods for analyzing human language. Therefore, new approaches including transformer models, have been invented to enhance the effectiveness of sentiment analysis [16]. There is always the issue of varied sentiments within a document since it has several expressions and changes its status. When analyzing text within the same document, it may be that different parts of the text convey opposing sentiments, which complicates the correct classification of the general sentiment of the document. This problem becomes especially acute in health-care-related materials where, for example, patients' experiences and feedback might range from enthusiasm to anger. The nature of sentiment was that a single document such as a healthcare document might comprise sentiments both positive and negative. It is therefore likely that variations such as these may not be well explained by traditional models so machines need to do less of such things and this implies less accuracy. Indeed, to address the current weakness, greater sophistication is required in the technical strategies applied for the analysis of sentiments in the healthcare context [17]. A potentially ongoing problem with achieving successful natural language interpretation pertains to an accurate determination of the tone and strength held in scores of documents in their entirety. Various approaches are being investigated to resolve this problem; specifically, the emphasis of the work is on detecting and handling context and conflicting valencies in texts. This approach the research is especially useful in such spheres as healthcare since the response can convey a whole range of emotions. Further development efforts are directed toward enhancing the overall efficacy of sentiment classification by capturing the nuances of document-level sentiment [18]. Moreover, many previous works on sentiment analysis assumed the use of the hand-crafted features which, in certain cases, hinders the identification of sophisticated patterns. Some of these handcrafted works are developed based on certain assumptions that fail to correspond to other types and changing language. Furthermore, these approaches also face challenges in efficiency in handling larger datasets which are normally slow in trials and not scalable. Therefore, they might not be the most appropriate to deal with the quantities of data produced in actual-world applications, such as healthcare. Sophisticated methods like deep learning models are a better cope in terms of scalability and even in terms of feature learning since the models learn features from the datasets.

The changes that came with transformers like BERT are revolutionizing the field of Natural Language Processing. Such models are very effective in understanding the positional or spatial significance of a word in a sentence and also encode these languages in a wider perspective than conventional models.

Since BERT works as a bidirectional model it is better to appreciate the meaning of the word based on the context. This has defined new standards for many tasks such as improving, the accuracy as well as the robustness of the sentiment analysis. Consequently, transformer-based programs are preferred for most NLP applications, specifically in the healthcare sector [19]. The self-attention-enhanced models are particularly remarkable at identifying the complex semantic information conveyed in a text. The self–attention mechanism enables the model to determine the contributions of a particular word to the entire context of a sentence. This will also make the transformer-based models such as BERT understand complicated language features and dependencies. Their capabilities in simple tasks such as sentiment analysis have delivered beyond the regular machine learning frameworks. For this reason, these models are today used in tasks where a deep understanding of the texts is needed, for instance, in the analysis of sentiment related to healthcare [17]. BERT and several similar models have learned how to use the language after being trained on a wide range of data resources. This I believe makes our models capable of learning a vast number of linguistic features and contextual information. It does so because BERT is highly proficient in a range of natural language processing undertakings such as sentiment analysis. Due to its capability to analyze the relationship between the words, such systems are very useful in complicated fields such as medicine. SA applications based on BERT have become a new benchmark for both accuracy and ease of use [20]. Namely, an advantage of sentiment classification is that BERT takes into account not only the given word but also the previous and the next words and phrases. This bidirectional processing enables BERT to capture both the right and left contexts of a word which is so important in determining sentiment. BERT performs exceptionally well when working with sentiments conspicuous by contextual factors in sentiment analysis. For instance, multipurpose terms or terms with specified emotions can be explained in a better way if BERT defines their environments. Hence, the use of BERT has reinforced the classification of sentiment in extensive textual content, especially in healthcare feedback [21]. The changes that came with transformers like BERT are revolutionizing the field of Natural Language Processing. Such models are very effective in understanding the positional or spatial significance of a word in a sentence and also encode these languages in a wider perspective than conventional models. Since BERT works as a bidirectional model it is better to appreciate the meaning of the word based on the context. 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Social media and patient feedback are useful forums of information that can be used by comprises of health care practitioners. When such information is analyzed by sentiment analysis, it allows healthcare organizations to be aware of the large volumes of unstructured data to specify patterns and trends regarding patient experiences. Sentiment analysis can also be used to capture new trends in patient or service feedback that may potentially be relevant to patient safety or service delivery. This approach ensures that issues that may very well go unnoticed if staff were to fill out the usual feedback forms are viewed and acted upon. In so doing it helps healthcare providers respond to patients' concerns effectively, and give them the best possible care [23]. The following concerns can be obtained from sentiment analysis of patient feedback information and used to inform planned efforts to respond to these complaints. It also allows nurses and other clinicians to identify what matters most in relationships and which risks are most important to reduce. It also provides an acceptable and valuable opportunity to support decision-making using STIS, for determining where the focus and improvement efforts should be targeted. This is true because by using big data, the healthcare organization can improve the experience of the patient. This improved outcomes, by getting higher patient satisfaction, and improving the quality of the care provided.

Hospitals face demanding issues when performing sentiment analysis in healthcare despite its various potential benefits. Medical terminology displays such complexity that it hinders the success of exact patient feedback analysis. Language subjectivity creates additional complexity because patients interpret emotional expressions differently. The task becomes more complex because different patients present unique experiences during healthcare contact. Specialized techniques become necessary to properly transform patient feedback into practical insights due to these complex challenges [24]. Healthcare sentiment analysis benefits from the continual increase in massive datasets which helps address current analysis challenges. Modern natural language processing models built on transformer architectures guarantee better processing and interpretation of difficult medical language. Advanced model systems deliver stronger contextual understanding which lets them process sophisticated patient feedback with better accuracy. Healthcare providers unlock better insights from patient data through the application of these methods. Healthcare organizations use this methodology to deliver decision support which enhances healthcare delivery while improving patient outcomes.

RESEARCH METHODOLOGY

The proposed model of this study is shown in Fig.1.

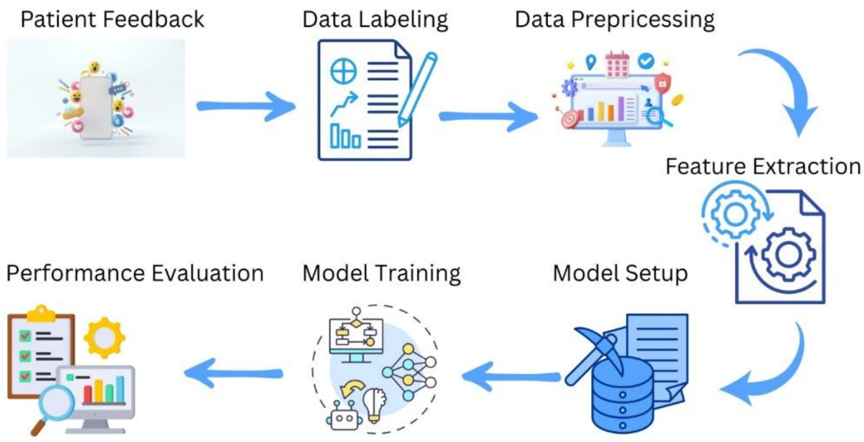

Fig.1. The Proposed Model

In this section of the research, the actual steps employed in the current study are described, particularly about the construction of the dataset. The tasks of preprocessing the data, making it fit for use in the analysis. The models examined in this work are also presented together with their applicability to sentiment analysis in the healthcare context. Moreover, the procedure for experimenting is provided whereby the equipment and processes applied in the analysis are described. Last but not least, the evaluation parameters used to measure the effectiveness of the models are outlined to avoid on part of the researcher being accused of having used statistically manipulated findings.

RESULTS AND DISCUSSION

Experiment-1 SVM

The classical models' best performance was by the SVM in terms of precision and the F1-score is 89% shown in Fig.2. This shows that it can correctly identify positive sentiment instances well. This is because it was able to generalize the data well thereby giving it better results. These metrics show the effectiveness of this architecture for sentiment analysis tasks.

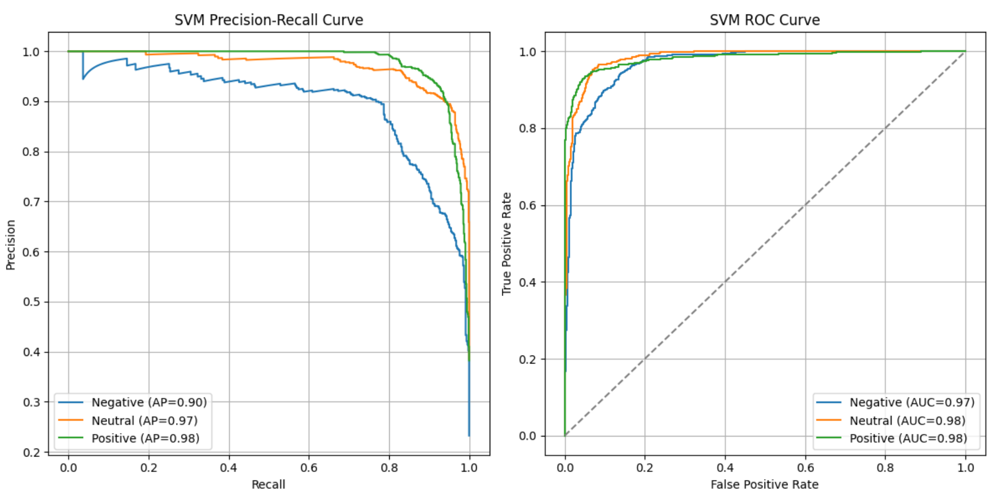

Fig.2. SVM Precision, Recall, & ROC Curve

Experimentt-2 Naive Bayes

The overall accuracy and the precision of the Logistic Regression model were lower than those of SVM. However, it proved to be more accurate in the neutral sentiment class. This shows that for balanced classification it is in a position to perform well. It remains easy to interpret the results, which is a big advantage when analyzing the data as shown in Fig.3.

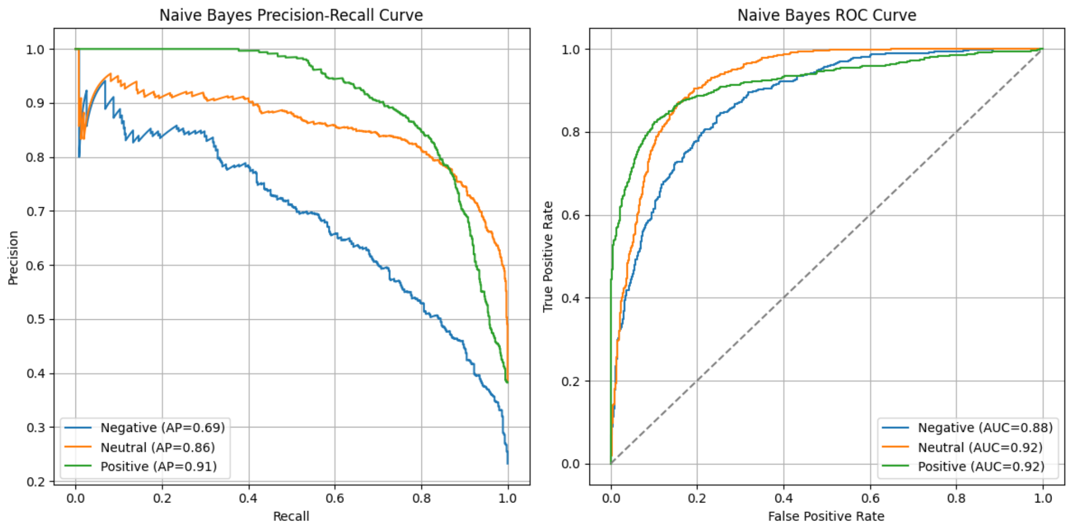

Fig.3. Naïve Bayes Precision, Recall, & ROC Curve

Experiment-3 Logistic Regression

The LR showed moderate performance in terms of both precision and recall for all classes albeit slightly lower recall than that of the SVM as shown in Fig.4.

Logistic Regression Precision Recall & ROC Curve (Graph No: 3)

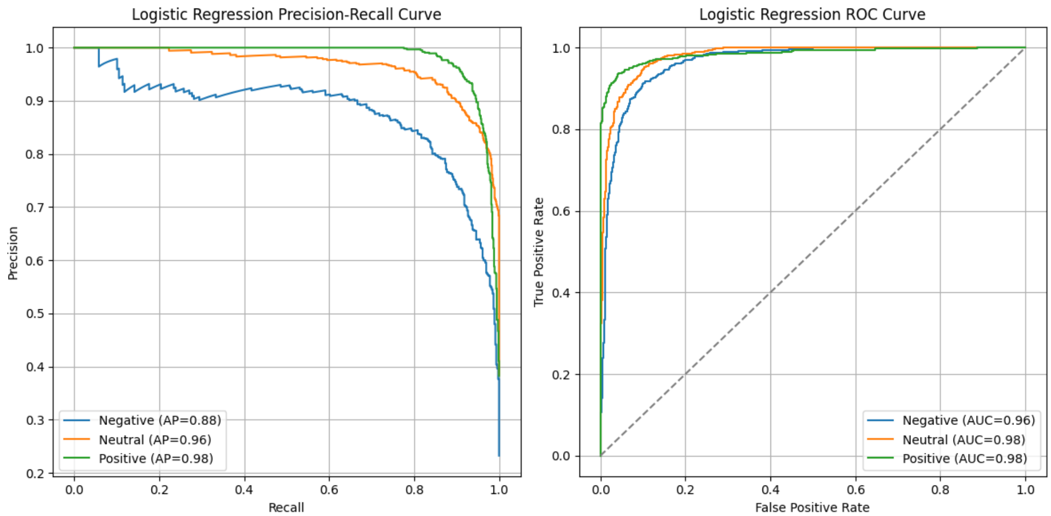

Fig.4. Logistic Regression Precision, Recall, & ROC Curve

Experiment4 BERT Fine-Tuning Performance

The fine-tuned BERT model was much better than the classical models with a test accuracy of 91.4%. This is the ability to apply BERT's features to better understand language patterns as well as the context in sentiment analysis. The proposed model outperformed all other models in all metrics such as precision, recall, and F1-score as shown in confusion matrix as in Fig.5.

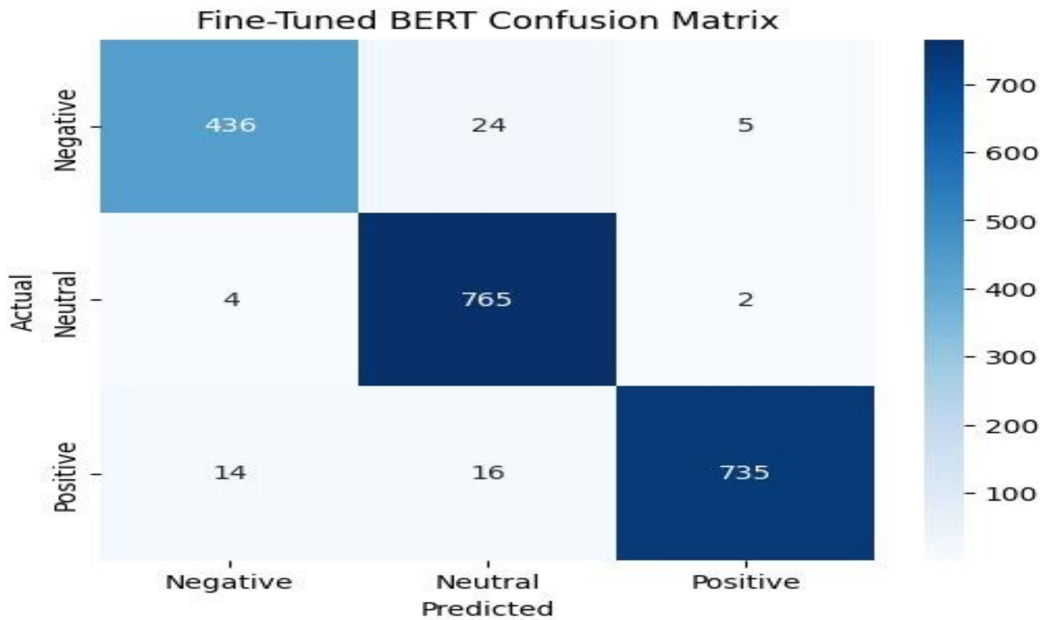

Fig.5. Confusion Matrix of Fine-Tuned BERT

CONCLUSION AND FUTURE WORK

This research demonstrates the potential of advanced sentiment analysis techniques, particularly the fine-tuned BERT model, in accurately interpreting patient sentiments from social media and healthcare websites to enhance patient safety and healthcare service delivery. While traditional machine learning models like SVM, Logistic Regression, and Naive Bayes performed moderately well, BERT outperformed them by capturing nuanced language features and achieving a 97% accuracy rate. Despite its superior performance, BERT's computational demands and limited interpretability present challenges for practical implementation. Therefore, integrating domain-specific models, improving efficiency, and incorporating explainability are crucial directions for future research to ensure the broader applicability of sentiment analysis in evidence-based healthcare decision-making.

The use of other areas where we will implement in the future are-oriented BERT models, for example, BioBERT or FineBERT, particularly for finance, can improve the accuracy by using knowledge from corporations used during the pre-training process. Perhaps, such models can better capture such subtleties that a general-purpose BERT model would overlook. It is revealed that the models should be tested on more extensive, various, and diverse corpora containing information from different sources, languages, and domains to understand their applicability and effectiveness fully. Results would further increase if data gathered from other cultures and regions were collected.

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