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IDENTIFYING TECHNICAL AND VOCATIONAL EDUCATION AND TRAINING (TVET) SENTIMENT FROM SOCIAL MEDIA USING MACHINE LEARNING APPROACH

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ABSTRACT: Technical and Vocational Education and Training (TVET) has become a key priority for the Malaysian government to enhance the system, better aligning it with industrial demands and workforce needs. The primary priority is to ensure that students and graduates acquire in-demand skills, thereby increasing their employability and creating more attractive job opportunities. Due to rapid technological advancements, social media has emerged as a powerful platform for public discourse where discussions on TVET programs, policies, and perceptions occur extensively. Among these platforms, Facebook is a widely used space for public interactions through posts and comments. This study employs sentiment analysis to analyse TVET-related discussions on Facebook, categorising sentiment into positive, neutral, and negative polarities. The Term Frequency-Inverse Document Frequency (TF-IDF) method is utilised to extract meaningful insights, and six classifiers, comprised of Support Vector Machine (SVM), Naïve Bayes (NB), Decision Tree (DT), Random Forest (RF), K-Nearest Neighbour (KNN), and Logistic Regression (LR), are applied. Using an 80%-20% training and testing split, results indicate that SVM achieves the highest accuracy performance, with a score of 0.62, outperforming other classifiers. Hence, this study provides valuable insights for policymakers and relevant stakeholders in the TVET ecosystem. By leveraging sentiment analysis and machine learning, decision-makers can better understand public perceptions and develop well-informed strategies to realign and enhance the TVET system.

ABSTRAK: Pendidikan dan Latihan Teknikal dan Vokasional (TVET) menjadi keutamaan kerajaan Malaysia bagi meningkatkan sistem agar lebih selaras dengan permintaan industri dan keperluan tenaga kerja. Keutamaan ini adalah bagi memastikan pelajar dan graduan memperoleh kemahiran yang diperlukan, meningkatkan kebolehpekerjaan serta mewujudkan lebih banyak peluang pekerjaan. Kepesatan kemajuan teknologi menyebabkan media sosial muncul sebagai platfom berpengaruh bagi wacana awam di mana perbincangan mengenai program, dasar, dan persepsi TVET berlangsung secara meluas. Antara platfom tersebut, Facebook menjadi medium terbanyak digunakan bagi interaksi awam melalui hantaran dan komen. Kajian ini menggunakan analisis sentimen bagi menganalisis perbincangan berkaitan TVET di Facebook dengan mengkategorikan sentimen kepada positif, neutral, dan negatif. Kaedah Frekuensi Dokumen Terma *Frequency-Inverse* (TF-IDF) digunakan bagi mengekstrak pandangan bermakna dan seterusnya menerapkan enam pengklasifikasi yang terdiri daripada Mesin Sokongan Vaktor (SVM), *Naïve Bayes* (NB), Pokok Keputusan (DT), Rawak *Forest* (RF), *K-Nearest Neighbour* (KNN), dan Regriasi Logistik (LR). Menggunakan peratusan data pembahagian latihan dan ujian sebanyak 80%-20%, dapatan kajian menunjukkan bahawa SVM mencapai prestasi ketepatan tertinggi dengan skor 0.62, mengatasi pengklasifikasi lain. Oleh itu, kajian ini memberi pandangan berharga kepada penggubal dasar dan pihak berkepentingan dalam ekosistem TVET. Dengan memanfaatkan analisis sentimen dan pembelajaran mesin, penggubal dasar dapat memperoleh pemahaman mendalam tentang persepsi awam dan membangunkan strategi berinformasi bagi menyelaras dan meningkatkan sistem TVET.

KEYWORDS: *TVET, Sentiment analysis, Machine learning*

1. INTRODUCTION

Technical and Vocational Education and Training (TVET) is a specialised education branch focusing on technology, sciences, and practical skills. It covers various education, training, and skill development across production, services, livelihoods, and occupational sectors. It gives students with the necessary knowledge and tools to pursue careers in various sectors, thereby contributing to business and societal progress [1]. More than just an educational framework, TVET plays a crucial role in building a skilled workforce and boosting national competitiveness. In Malaysia, a well-established TVET ecosystem is a key driver of socio-economic development, addressing persistent challenges like dependency on foreign labor and the mismatch between industry demand and workforce supply. As a result, TVET serves as a strategic pillar in preparing individuals for a dynamic and rapidly evolving job market [2].

With the rise of digital communication, social media has become a powerful platform for TVET promotion, allowing stakeholders, including students and the public, to share experiences, exchange ideas, and engage in discussions [3]. A study by [4] highlighted that social media facilitates effective TVET delivery, enabling instructors to transcend traditional boundaries and provide teaching and learning anytime and anywhere. Additionally, platforms like Facebook and Twitter serve as primary channels for knowledge dissemination, often rivaling traditional media [5].

Given the vast volume of text and opinions generated on social media, sentiment analysis has emerged as a valuable approach to decoding public perceptions of TVET. This method enables the extraction of unstructured data to analyse users' opinions, emotions, attitudes, and perspectives on TVET-related topics [6]. Beyond its analytical function, sentiment analysis is an influential decision-making tool, offering insights into public sentiment regarding services, policies, and programs while identifying the emotional tone embedded in textual data [7], [8].

This study is unique in its contextual emphasis on Malaysian TVET, an under-represented field in sentiment analysis literature. Malaysia's TVET ecosystem faces enduring issues, including an unfavourable public perception of TVET as a second-choice tertiary pathway, fragmented governance across several ministries, and a substantial disparity between graduate competencies and industry demands. Hence, this study leverages a machine learning approach to analyse sentiment from social media platforms, assessing public opinion discourse on TVET. By comparing six classifiers, including Support Vector Machine (SVM), Naïve Bayes (NB), Decision Tree (DT), Random Forest (RF), K-Nearest Neighbours (KNN), and Logistic Regression (LR), this study evaluates their effectiveness in classifying sentiments based on performance metrics including accuracy, recall, precision, and F1-score. Through this approach, this study aims to identify the most reliable classifiers for sentiment classification and contribute valuable insights to policymakers, educators, and stakeholders in the TVET ecosystem by realigning TVET strategies, strengthening institutional credibility, and improving graduate preparedness.

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2. RELATED WORKS

Sentiment analysis utilising a machine learning approach has been extensively employed across multiple sectors, including banking, politics, hospitality, entertainment, and education. Many researchers have used this approach to derive insights from textual data and inform decision-making. A sentiment study of consumer feedback on mobile banking applications within the finance sector was conducted by [9] to identify key phrases associated with banking services. Their results demonstrated that SVM surpassed NB in all performance metrics, attaining an accuracy of 97.1%, precision of 97.2%, recall of 97.1%, and F1-score of 97.2%. This underscores SVM's exceptional capacity to analyze client input, making it an invaluable tool for banking service providers to improve the user experience.

A political sentiment study examined the public's perceptions of presidential candidates Joe Biden and Donald Trump during the 2020 United States election campaign [10]. The study harnessed Twitter data for sentiment analysis and employed machine learning classifiers such as Logistic Regression (LR), Random Forest (RF), and K-Nearest Neighbors (KNN). LR exhibited the highest performance of the classifiers evaluated, obtaining an accuracy of 74.3%. The study highlights the efficacy of machine learning in examining political speech and forecasting public sentiment patterns.

Understanding public perceptions of services is crucial for promptly and effectively addressing consumer concerns. A sentiment analysis was performed in [11] by collecting reviews from the TripAdvisor application. Their study concentrated on negative feedback and low-rated reviews, utilizing several machine learning classifiers, including Support Vector Machine (SVM), Naive Bayes, XGBoost, Logistic Regression, and Random Forest. Their findings demonstrated that SVM exhibited remarkable performance, with an accuracy rate of 76%, confirming its effectiveness in evaluating internet reviews. This discovery provides substantial insights for strategic decision-making in the hospitality industry, allowing organisations to tackle client problems proactively.

Machine learning was used in [12] to assess sentiment towards Malaysian places of attraction in the tourism sector. The data was gathered from Twitter and comprised Malay-language text processed with the Malaya corpus. The study evaluated three supervised learning classifiers: Support Vector Machine (SVM), Random Forest (RF), and Naive Bayes (NB). Their findings revealed that SVM achieved the highest accuracy, recall, precision, and F1 score. SVM attained the best accuracy at 92.40%, Naive Bayes at 89.65%, and Random Forest at 88.55%.

Sentiment analysis has also been crucial in comprehending students' viewpoints on online education, especially during the COVID-19 pandemic. [13] examined students' perceptions of online learning through machine learning-based sentiment analysis. Their study showed that the Random Forest (RF) classifier surpassed other classifiers such as Naïve Bayes (NB), Support Vector Machine (SVM), and Decision Tree (DT) regarding accuracy, recall, and precision. These findings underscore the capacity of machine learning to augment educational insights, enabling educators to customize online learning experiences according to students' feedback.

3. METHODOLOGY

This study follows a structured multi-step method, as illustrated in Fig. 1. The process consists of data collection, text preparation and pre-processing, feature extraction, sentiment classification using a machine learning approach, and performance evaluation.

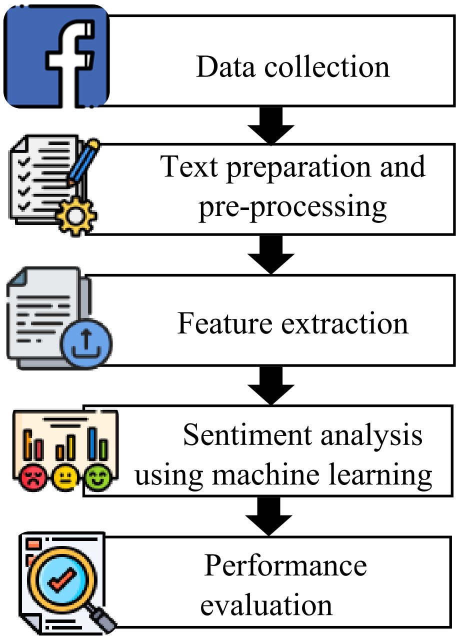

Figure 1. Workflow of sentiment analysis using machine learning

3.1. Data Collection

In this study, the data were collected from publicly accessible Facebook groups and media pages by focusing on contents that engage in active discussions on TVET-related topics. For media pages, only posts and comments specifically addressing TVET issues were included to ensure the relevance of the dataset. The data collection process complied with Facebook's terms of service, and no private user information or personal identifiers were gathered. The data collection process spanned from April 2021 to March 2023 and was facilitated by Facepager and Apify, web scraping tools. Apify, an automated web scraping platform, retrieved and exported unstructured data in .csv format. Meanwhile, Facepager, a tool developed by [14], utilised application programming interface (APIs) and web scraping techniques to retrieve publicly accessible data from YouTube, Facebook, and Twitter.

3.2. Text preparation and pre-processing

Before the analysis process, a data pre-processing stage was carried out to ensure the data quality was suitable for the text mining technique. During data pre-processing, data cleaning and normalization techniques were implemented to improve the quality of sentiment classification. The text preparation process was also carried out at this stage, which involved removing or correcting unnecessary elements such as punctuation, misspellings, abbreviations, and informal language.

The dataset comprised bilingual text written in Malay and English. The Malay data were translated into English using Google Translate to maintain uniformity in sentiment classification. The translated data were further validated using sentiment lexicons to ensure that the sentiment polarity remained consistent and semantically accurate. In addition, the dataset exhibits class imbalance, and no resampling has been implemented to maintain the real sentiment distribution visible in public discussion. This option offers a more reliable classifier performance evaluation in situations similar to real-world sentiment variations. Moreover, the pre-processing phase involved several steps, including lowercasing all text to maintain consistency, removing punctuation and special characters to eliminate noise, and filtering out

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stop words to enhance meaningful content extraction. Following this process, 1,304 posts were deemed suitable for analysis.

3.3. Feature Extraction

To convert textual data into a numerical format for machine learning analysis, this study employed the Term Frequency-Inverse Document Frequency (TF-IDF) method. Feature extraction is crucial in transforming raw text into a structured presentation [15]. TF-IDF operates based on two components: Term Frequency (TF), which measures the importance of a word within a document, and Inverse Document Frequency (IDF), which assesses the significance of a word across the entire dataset, thereby reducing the influence of common words [16]. This method was chosen due to its proven effectiveness in improving accuracy metrics and its ability to capture the meaningful importance of words in the text [17].

3.4. Sentiment Analysis using Machine Learning

This study utilised Python-based machine learning libraries to conduct sentiment analysis on the pre-processed text. Six machine learning classifiers were employed, including Support Vector Machine (SVM), Naïve Bayes (NB), Decision Tree (DT), Random Forest (RF), K-Nearest Neighbours (KNN), and Logistic Regression (LR).

3.5. Performance Evaluation

The classification models were evaluated using four key performance metrics as shown in Equations (1) to (4). Accuracy, as expressed in Eq. (1), measures the proportion of correctly predicted sentiments relative to the total number of instances. In addition, precision represented in Eq. (2) is the proportion of correctly identified positive cases among all the instances predicted as positive. Meanwhile, recall evaluates the classifier's ability to correctly identify true positive instances from the total actual positive instances in the dataset as defined in Eq. (3). F1-score provides a harmonic mean between precision and recall, providing a balanced measure of the classifier's overall performance as computed in Eq. (4). By employing these evaluation metrics, the study ensures a comprehensive performance evaluation and facilitates the identification of the most effective machine learning classifier for TVET sentiment analysis where TP denotes the number of correctly classified positive values, TN the correctly classified negative values, FP the incorrectly classified positive values, and FN the incorrectly classified negative values.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

$$\text{F1} - \text{Score} = \frac{2 \times precision \times recall}{precision+recall} \tag{4}$$

4. RESULT AND ANALYSIS

This study classified 1,304 posts and comments from Facebook using SVM, NB, DT, RF, KNN, and LR classifiers. Referring to the performance of multiple classifiers, SVM attained the highest accuracy of 0.62, closely followed by LR at 0.61. The classifiers of KNN got the lowest accuracy at 0.38, showing their ineffectiveness in categorising TVET sentiment. Among the classifiers, SVM consistently exceeds other classifiers, demonstrating comparable performance across all sentiment categories. The NB and RF attained an accuracy of 0.55, demonstrating competitive outcomes although exhibiting diverse performance among various sentiment categories. Fig. 2 depicts the accuracy performance of all utilised classifiers, offering a comparative analysis of their effectiveness in sentiment classification.

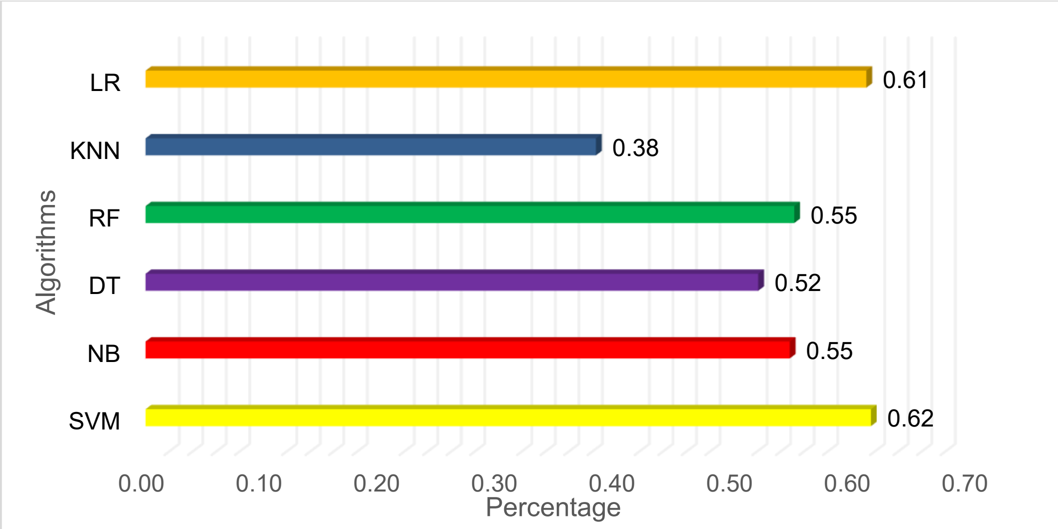

Figure 1. Accuracy performance of machine learning classifiers for TVET sentiment classification

Although SVM demonstrated the highest accuracy, it appears lower compared to prior findings in sentiment analysis studies. Such low accuracy in sentiment analysis may be attributable to many factors, among them the issue of word ambiguity and context dependence. For example, the word ‘opportunity’ may be positive in the context of education and its value to a person, but negative when describing employment, particularly for specific sectors. Lexicon-based approaches often fail to capture these nuances, leading to misclassification.

Furthermore, the dataset derived from Facebook exhibits many informal terms and languages, bilingual expressions, and sentiment ambiguity. These factors also often impair reliability. The SVM confusion matrix in Table 1 indicates that the most accurate classifications are found along the diagonal, with 36 correctly predicted positive instances, 53 neutral instances, and 71 negative instances. However, misclassification occurred in 16 positive instances, which were erroneously labeled as negative, while the 29 neutral instances were incorrectly predicted as negative. These errors indicate overlapping sentiment expressions, particularly between neutral and other polarities, which are frequently observed in social media discussions.

Table 1. SVM confusion matrix

	Predicted: Positive	**Predicted: Neutral**	**Predicted: Negative**
True: Positive	36	8	16
True: Neutral	15	53	29
True: Negative	14	19	71

A comprehensive analysis of precision, recall, and F1-score for each classifier across positive, neutral, and negative polarities is presented in Table 2. For the positive sentiment, SVM and NB achieved the highest precision scores of 0.74 and 0.70, respectively. However, recall scores for positive polarity remain consistently low across all classifiers, with DT and KNN exhibiting the lowest performance scores at 0.17 and 0.05, respectively. This indicates that although these classifiers may accurately detect certain instances of positive sentiment, they exhibit poor recall, missing a substantial number of positive examples.

Regarding neutral sentiment, both SVM and LR achieved the highest precision scores of 0.66 and demonstrated comparable performance. In contrast, SVM recorded an F1-score of 0.64, indicating an effective classification of neutral polarity. Meanwhile, the most effective classifier for negative polarity is SVM, with an F1-score of 0.69, followed by NB with 0.63. In contrast, KNN exhibited the lowest performance, achieving an F1-score of 0.04, which highlights its inability to detect negative sentiment effectively.

Overall, SVM is the most effective classifier, recording an overall accuracy of 0.62 and outperforming other classifiers. While LR showed an accuracy of 0.61, it indicated stable performance in sentiment classification. Additionally, NB and RF demonstrated moderate performance, gaining competitive F1-scores, particularly in the detection of negative sentiment. On the other hand, KNN displayed the lowest performance, encountering substantial difficulties in reliably identifying positive and negative sentiment. Based on these findings, selecting classifiers for TVET sentiment analysis must emphasize classifiers that balance precision and recall, as inaccurate classification may result in distorted sentiment representation and misinterpretation of public opinion.

Table 2. Machine learning algorithms evaluation metrics

Algorithm	Acc.	Positive			Neutral			Negative		
		P	R	F	P	R	F	P	R	F
SVM	0.62	0.74	0.47	0.57	0.66	0.62	0.64	0.61	0.78	0.69
Naive Bayes	0.55	0.70	0.27	0.39	0.57	0.44	0.50	0.51	0.81	0.63
Decision Tree	0.52	0.63	0.17	0.25	0.48	0.63	0.55	0.56	0.62	0.59
Random Forest	0.55	0.50	0.18	0.27	0.56	0.55	0.55	0.55	0.77	0.64
K-Nearest Neighbors	0.38	0.60	0.05	0.09	0.38	0.98	0.54	0.67	0.02	0.04
Logistic Regression	0.61	0.60	0.48	0.54	0.66	0.54	0.59	0.59	0.76	0.66

Acc.: accuracy; P: precision; R: recall; F: F1-score

5. CONCLUSION

This study explored sentiment classification using a machine learning approach in Technical and Vocational Education and Training (TVET) discussions on social media. We employed six classifiers, SVM, NB, DT, RF, KNN, and LR, to classify the sentiment into positive, neutral, and negative categories. The Term Frequency-Inverse Document Frequency (TF-IDF) was employed to extract relevant features to enhance the dataset's categorization capabilities.

The results revealed that SVM outperformed other classifiers, achieving the highest accuracy of 0.62 and demonstrating robust performance across all sentiment categories. Logistic regression followed closely with an accuracy of 0.61, while Naive Bayes and Random Forest attained moderate accuracy with 0.55. In contrast, KNN exhibited the lowest performance with an accuracy of 0.38, indicating its inefficacy in handling sentiment classification for TVET discussion. The precision, recall, and F1-score evaluations further emphasised SVM's superiority, particularly in accurately classifying negative and neutral sentiments.

Regarding the insights from the sentiment analysis findings, it is evident that across all classifiers with higher accuracy, positive sentiments towards TVET dominate. This highlights the public's expectations of TVET, particularly its role in helping younger generations access better education through vocational skills. Further thematic analysis is needed to explore vocational education's perceived benefits and challenges.

Despite its promising results, this study has specific limitations. The dataset is limited to Facebook posts and comments, which may not sufficiently encompass sentiment across other online platforms. Moreover, traditional machine learning models have limitations in addressing the contextual intricacies, sarcasm, and dynamic nature of language in user-generated content. Therefore, future studies should explore the use of a hybrid approach, combining lexicon-based and machine learning methods to enhance sentiment classification performance.

The findings of this study have considerable implications for policymakers, educators, and stakeholders within the TVET ecosystem. Social media sentiment analysis provides strategic value for TVET stakeholders in Malaysia. The collected sentiment trends can assist decision-makers in recognising primary issues, reformulating institutional narratives, optimising curriculum alignment, and ultimately promoting graduate employability. As Malaysia seeks to establish TVET as a leading pathway for industrial preparedness, data-driven sentiment research can effectively align policy with public perception.

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