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Sentiment Analysis of Digital Ethics in YouTube Islamic Preaching Videos Using Support Vector Machine

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Abstract

The rapid expansion of Islamic preaching in the digital sphere, particularly through YouTube, calls for a deeper understanding of communication ethics as reflected in user responses. This study analyzes the sentiments expressed in comments on Islamic preaching videos to identify patterns of digital ethics within online communities. The research employs a Support Vector Machine (SVM) classification model with TF-IDF feature representation. Data were collected from YouTube comments and processed through several preprocessing stages, including text cleaning, case normalization, tokenization, stopword removal, and stemming, before being manually labeled into three sentiment categories: positive, negative, and neutral. Testing on 22 data samples shows that the SVM model achieved an accuracy of 77.27%, with the highest performance observed in the neutral category. Misclassification in the positive and negative categories was mainly influenced by data imbalance and linguistic variations commonly found in religious discourse. These findings indicate that SVM combined with TF-IDF is reasonably effective for sentiment analysis in the context of digital Islamic preaching; however, improvements in data balance and the incorporation of contextual features are necessary to enhance classification performance. Overall, this study provides an initial insight into audience response patterns toward digital Islamic preaching and contributes to the development of digital ethics research in Islamic communication studies.

I. INTRODUCTION -

The rapid advancement of information and communication technology has fundamentally transformed the ways individuals connect, interact, and exchange information across social, cultural, and religious domains. This transformation has also reshaped Islamic religious practices, particularly in the context of preaching and religious gatherings. Traditionally, Islamic sermons (pengajian) were conducted in mosques, pesantren, or community halls, requiring physical presence and limiting participation to specific geographical locations. However, the digitalization of communication has enabled Islamic teachings to

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transcend spatial and temporal boundaries, allowing religious messages to reach broader audiences through online platforms [1].

The shift toward digital preaching signifies a profound change in how Islamic knowledge is disseminated and consumed. Through online platforms, religious educators can deliver sermons to audiences of diverse ages, social backgrounds, and regions simultaneously. Among various digital platforms, YouTube has emerged as one of the most dominant media for sharing Islamic preaching content due to its audiovisual capabilities, accessibility, and interactive features. The platform allows da'i and religious scholars to archive sermons, distribute content asynchronously, and engage audiences through features such as likes, shares, and comment sections. This evolution demonstrates a transition from conventional, one-directional preaching to participatory digital religious communication that encourages immediate audience feedback and interaction. Despite its advantages, the rise of YouTube as a medium for Islamic preaching also introduces complex challenges, particularly regarding the quality of discourse and ethical behavior within its comment sections. Comment sections on YouTube function as virtual public spheres where users are free to express opinions, criticisms, praises, or disagreements related to religious content. While such openness fosters democratic dialogue and inclusivity, it also creates opportunities for unethical behavior, including disrespectful language, misinterpretation of religious teachings, provocation, and moral insensitivity. These dynamics raise critical concerns about how digital ethics are practiced in online religious spaces.

Digital ethics refers to a set of moral principles governing behavior in digital environments, including norms of politeness, respect, tolerance, accountability, and responsibility in online communication. In the context of Islamic preaching, digital ethics becomes particularly significant, as religious discourse carries moral authority and influences social behavior. Several scholars argue that digital da'wah must be accompanied by clear ethical guidelines to ensure that the objectives of preaching promoting moral values, unity, and social harmony are not undermined by harmful interactions [2]. Without ethical regulation, online religious discussions risk devolving into conflict, misinformation, and moral degradation. Research on online communication ethics has increasingly emphasized the importance of maintaining constructive discourse in interactive platforms such as YouTube. [3] highlights that comment sections are not merely technical features but social spaces that shape public perception and collective morality. In religious contexts, the obligation to maintain ethical interaction becomes even more critical, as comments may reflect broader attitudes toward religious authority, piety, and moral responsibility. Consequently, the ethical quality of interactions in YouTube comment sections serves as an important indicator of how religious values are internalized and practiced in digital environments.

From an Islamic ethical perspective, digital communication poses unique challenges. Issues such as the spread of hoaxes, digital gossip (ghibah), slander (fitnah), and hostile speech contradict fundamental Islamic teachings that emphasize honesty, respect, and social cohesion. [4] argue that the digital sphere necessitates a moral framework grounded in Islamic principles to guide ethical behavior online. Such a framework is essential to prevent the erosion of Islamic values in digital interactions and to promote responsible engagement with religious content.

In practice, scholars have suggested the implementation of ethical education and digital guidelines for online preachers and audiences as an effective strategy to improve the quality of online religious interactions. This includes educating users on respectful communication, critical engagement, and moral accountability in digital spaces. Analyzing user comments on digital da'wah platforms, therefore, becomes an essential step in assessing how Islamic moral values manifest in online discourse. In parallel with ethical concerns, sentiment analysis has emerged as a widely adopted method for examining public opinion and emotional tendencies in digital communication. Sentiment analysis enables researchers to classify textual data into sentiment categories such as positive, neutral, and negative, providing insights into public attitudes toward various topics. In the context of religious communication, sentiment analysis offers a systematic approach to understanding how audiences emotionally and ethically respond to Islamic preaching content. Numerous studies have applied sentiment analysis to examine social, political, and religious discourse on social media platforms. Various machine learning techniques have been utilized, including Naïve Bayes, K-Nearest Neighbor (KNN), Decision Trees, and Support Vector Machine (SVM). [5] demonstrated that

Naïve Bayes performs adequately in classifying sentiments from YouTube sermon comments, particularly for datasets with relatively simple linguistic structures. However, other studies suggest that Naïve Bayes may struggle with complex, context-rich, and lengthy texts commonly found in religious discourse. [6] emphasize that SVM is particularly effective in handling high-dimensional text data and complex linguistic patterns. SVM constructs optimal hyperplanes that maximize class separation, making it well-suited for sentiment classification tasks involving nuanced expressions and varied vocabulary. [7] further confirm the superiority of SVM in classifying sentiment within religious texts, highlighting its robustness and generalizability across different domains. The effectiveness of SVM is further enhanced when combined with Term Frequency–Inverse Document Frequency (TF-IDF) for feature extraction. TF-IDF transforms textual data into numerical representations by weighting terms based on their frequency and significance within a corpus. This approach allows machine learning models to capture semantic relevance while reducing the influence of commonly occurring but less informative words. Numerous empirical studies support the efficiency of TF-IDF and SVM integration in sentiment analysis tasks involving unstructured and semantically complex data.

[8] demonstrated the reliability of this approach by achieving an accuracy rate of 71.11% in analyzing public opinion regarding the International Student Mobility Award (IISMA) program on the X/Twitter platform. Similarly, [9] reported accuracy levels exceeding 74% when applying TF-IDF and SVM to YouTube comment sentiment analysis. These findings underscore the suitability of SVM-based models for analyzing digital discourse, including religious communication. Despite the growing body of research on digital da'wah, existing studies predominantly focus on content delivery strategies, audience engagement, and digital literacy enhancement. [10] for instance, emphasize the importance of concise and visually appealing Islamic content on Instagram to attract younger audiences. [11] and [12] highlight the role of digital literacy in enabling Muslim communities to adapt to rapidly evolving online platforms. However, these studies pay limited attention to the ethical quality of user interactions within comment sections. Research specifically examining digital ethics in responses to Islamic preaching remains relatively scarce. [13] explore emotional discomfort within pesantren environments influenced by social media but do not address ethical communication in online religious interactions. Similarly, [14] emphasize the importance of digital competence in filtering information without explicitly discussing ethical discourse in Islamic da'wah contexts. This gap indicates a pressing need for systematic research on how Islamic moral principles such as politeness, respect, unity, and social responsibility are reflected in online discussions surrounding religious content.

This study addresses this research gap by focusing on sentiment analysis of YouTube comments on Islamic preaching videos as a means of evaluating digital ethics. Rather than merely assessing public reactions to sermon content, this research examines how sentiments expressed in user comments reflect ethical communication practices. By categorizing sentiments into positive, neutral, and negative classes, the study provides insights into the moral tone and quality of digital interactions within Islamic preaching spaces. The focus on digital ethics distinguishes this research from prior studies that prioritize engagement metrics or content effectiveness. This approach aligns with [15], who emphasize the importance of value-based communication analysis in digital da'wah research. The methodological framework employs Support Vector Machine as the core classification model due to its proven reliability in handling linguistically diverse and context-sensitive textual data. The contributions of this study extend to both theoretical and practical domains. From a theoretical perspective, it enriches the field of Islamic communication studies by integrating computational methods with ethical analysis. Practically, the findings offer valuable guidance for preachers, educators, and policymakers in designing digital da'wah strategies that prioritize ethical discourse, moral accountability, and social harmony. [16] asserts that social media serves as a crucial arena for character formation through online interaction aligned with Islamic values.

Furthermore, this research provides a framework for identifying ethical challenges in online religious communication and assessing the impact of digital preaching on public discourse quality. By mapping sentiment patterns and ethical tendencies among Muslim audiences in Indonesia, the study contributes to a deeper understanding of how digital platforms shape religious interaction. Ultimately, this research underscores the importance of fostering ethical digital environments that support constructive dialogue, religious understanding, and moral integrity in contemporary Islamic preaching.

II. RELATED WORKS

2.1. Digital Transformation of Islamic Preaching

The transformation of Islamic preaching in the digital era has been widely discussed in contemporary communication and religious studies. Digital platforms have significantly altered the structure, reach, and dynamics of da'wah activities, shifting them from localized, physical gatherings to globally accessible online environments. Scholars such as [17] and [18] argue that digital religion is not merely a technological shift but a reconfiguration of religious authority, interaction, and participation. In this context, YouTube has emerged as a dominant platform for Islamic preaching due to its audiovisual affordances and interactive features. Several studies highlight YouTube's effectiveness in disseminating Islamic knowledge to diverse audiences. [10] emphasize that digital preaching on YouTube allows religious messages to be archived, replayed, and shared, enhancing long-term engagement. [11] further note that YouTube enables preachers to adapt sermon styles to digital audiences, incorporating storytelling, visual cues, and concise messaging. However, these studies primarily focus on content delivery and audience reach, rather than ethical interaction among viewers.

2.2. YouTube Comment Sections as Digital Public Spaces

YouTube comment sections have been conceptualized as digital public spheres where users engage in discourse, negotiation of meaning, and identity expression [19] [20]. In religious contexts, these spaces serve as arenas for expressing agreement, appreciation, critique, and theological debate. [3] stresses that comment sections are not neutral spaces, they actively shape public morality and collective religious understanding. Research by [21] and [22]suggests that digital public spaces require ethical norms to prevent discourse degradation. Without ethical guidance, comment sections may become sites of hostility, misinformation, or moral erosion. In Islamic preaching contexts, this concern is amplified because discourse is closely tied to moral and spiritual values. Despite this, existing literature often treats comment sections as supplementary engagement tools rather than core objects of ethical analysis.

2.3 Digital Ethics in Online Religious Communication

Digital ethics has emerged as a critical framework for evaluating online behavior, encompassing respect, responsibility, accountability, and moral awareness in digital interactions [23]. From an Islamic perspective, digital ethics aligns with principles such as adab (proper conduct), ukhuwah (brotherhood), and amanah (responsibility). [4] argue that digital platforms require ethical reinterpretation grounded in Islamic moral teachings to address challenges such as hoaxes, digital gossip, and hostile speech. Several studies explore ethical challenges faced by Muslim communities in online environments. [13] examine emotional discomfort and moral tension in pesantren environments influenced by social media, while [14] emphasize digital literacy as a means of filtering information. However, these studies stop short of systematically analyzing ethical sentiment in user-generated responses to Islamic preaching. This gap highlights the need for empirical approaches that directly examine how ethical values manifest in online religious discourse.

2.4 Sentiment Analysis in Religious and Social Media Studies

Sentiment analysis has become a prominent method for examining public opinion and emotional expression in digital communication. [24] and [25] define sentiment analysis as the computational identification and classification of opinions expressed in text. In religious contexts, sentiment analysis provides insights into how audiences emotionally respond to spiritual messages and moral teachings. [5] demonstrate the applicability of sentiment analysis for classifying responses to Islamic sermon videos on YouTube using Naïve Bayes. Their findings suggest that sentiment analysis can effectively capture general emotional tendencies in religious discourse. However, Naïve Bayes models often assume word independence, limiting their performance when dealing with complex and context-rich religious language. Other studies extend sentiment analysis to broader social and ethical topics. [26] and [27] apply sentiment analysis to detect nuanced emotional expressions in social media discussions, emphasizing the importance of robust classification models. These findings support the relevance of sentiment analysis as a methodological foundation for examining ethical discourse in online religious settings.

2.5 Support Vector Machine for Text Classification

Support Vector Machine (SVM) is widely recognized as one of the most effective machine learning algorithms for text classification tasks. According to [28] and [29] ,SVM performs well in high-dimensional feature spaces and is particularly suitable for sparse text data. [6]) confirm that SVM outperforms several traditional classifiers when processing long and semantically complex texts. In religious discourse analysis, SVM has demonstrated strong performance due to its ability to capture subtle distinctions in sentiment. [7] show that SVM achieves higher accuracy than KNN and Naïve Bayes in classifying religious sentiment. Similarly, [9] report that SVM combined with TF-IDF achieves accuracy exceeding 74% in YouTube comment sentiment analysis.

2.6 TF–IDF as Feature Representation

Term Frequency–Inverse Document Frequency (TF-IDF) remains one of the most widely used feature extraction techniques in text mining [30]. TF-IDF assigns weights to terms based on their importance within a corpus, enabling machine learning models to distinguish meaningful words from common but less informative ones. [31] argue that TF-IDF is particularly effective for processing user-generated content with diverse linguistic structures, informal expressions, and varying word usage patterns commonly found on social media platforms.

[8] demonstrate that combining TF-IDF with SVM significantly improves classification performance in social media sentiment analysis. In the context of Islamic preaching comments, TF-IDF helps reduce the dominance of frequently occurring religious terms while preserving words that carry sentiment-related meaning. By reducing noise and emphasizing semantically relevant terms, TF-IDF enhances the robustness and interpretability of sentiment classification models, making it an appropriate feature representation for analyzing ethical communication patterns in digital religious environments.

2.7 Research Gap and Contribution

Despite extensive research on digital preaching, social media engagement, and sentiment analysis, few studies integrate these domains to examine digital ethics in Islamic preaching contexts. Most existing works focus on content strategies, digital literacy, or emotional responses, rather than ethical interaction patterns within comment sections. This limitation underscores the novelty of analyzing digital ethics through sentiment classification of YouTube comments. By employing SVM-based sentiment analysis, this study bridges communication ethics, Islamic studies, and computational linguistics. It provides a structured approach to assessing ethical discourse in digital religious environments, offering both theoretical insights and practical implications for ethical digital da’wah, particularly in understanding how audience interactions reflect moral restraint, respect, moderation, and responsible communication practices in large-scale, user-generated online religious spaces.

2.8 Summary of Related Works and Conceptual

Previous investigations have shown that examining user comments on digital platforms primarily emphasizes textual analysis, sentiment assessment, and mapping discussion patterns through the application of machine learning methodologies. The results provide a theoretical foundation for systematically classifying comment data to generate more organized information. Previous research has also demonstrated the need for models that are adept at accommodating linguistic variations, contextual nuances, and conversational dynamics. Based on this mapping, the conceptual framework of this study is developed by combining text analysis, sentiment assessment, and classification algorithms, aiming to produce a model that more accurately reflects the characteristics of comments on YouTube. This theoretical framework outlines data preprocessing, feature extraction, model training, and performance evaluation as essential components in creating an empirical and accountable analysis.

Figure 1. *Research Framework of Sentiment Analysis for Digital Ethics in YouTube Islamic Preaching*

III. METHODS

This study analyzes user responses to various Islamic preaching videos on YouTube to identify patterns in the application of digital ethical norms in religion-related interactions. The analysis aims to depict patterns of religious expression, types of moral appeals, and trends in communication behavior observed in the comments section as elements of preaching dynamics in the digital environment. To achieve this goal, the study adopts a quantitative-descriptive method reinforced by sentiment analysis techniques using machine learning, specifically the Support Vector Machine (SVM) algorithm, to produce an accurate model.

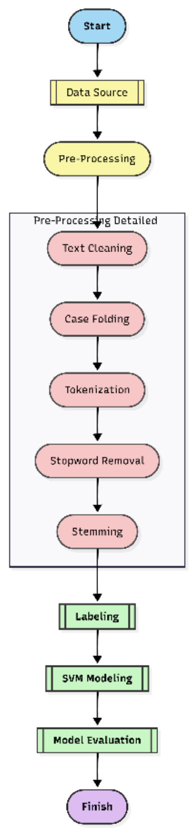

Figure 2 *Research Flow Diagram*

2.1 Data Source

The data in this study was taken from YouTube user comments collected from several dakwah videos. Data collection was carried out using the youtube-comment-downloader in a Python environment, and the results were saved in a .csv file for easier processing. The analysis process was conducted on the Google Colab platform, supported by various libraries such as pandas, regex, emoji, scikit-learn, wordcloud, and matplotlib to facilitate data processing and visualization. In this study, the tool used was a computational model based on Support Vector Machine (SVM), combined with the TF-IDF (Term Frequency–Inverse Document Frequency) representation technique, which functions to categorize comments into three sentiment classes: positive, negative, and neutral.

2.2 *Pre – Proccesing* Data

At this stage, raw YouTube comments, which serve as the basic data, are processed through various cleaning steps. The aim is to remove parts that could interfere with the accuracy of sentiment analysis. The process includes text normalization, character removal, duplicate comment filtering, and handling of punctuation and emoticons. Thus, the data ultimately becomes more consistent, organized, and reflective of reality, which can enhance the reliability of sentiment analysis results. The following are the preprocessing steps in this study.

1) Text cleaning is the process of removing disruptive elements in comments such as excessive punctuation, symbols, numbers, Uniform Resource Locator (URL), and non-alphabet characters.
2) Case folding functions to standardize all letters into a single form.
3) Tokenization functions to break sentences into word units.
4) Stopword removal functions to eliminate common words that do not carry sentiment meaning.
5) Stemming is the process of reducing words to their base form.

2.3 *Labelling*

At this stage, comments that have gone through the text-cleaning process are manually labeled to form a dataset that can be used for training a sentiment analysis model. Each comment is grouped according to style into three categories: positive, negative, and neutral. This step is carried out to ensure that the support vector machine (SVM) model has a clear understanding of how to distinguish sentiment patterns and is capable of identifying forms of religious interaction and digital ethics practices that appear in comments on da'wah videos on YouTube.

2.4 Sentiment Modeling and Classification

The modeling stage in this study focuses on grouping attitudes in YouTube comments related to Islamic preaching by utilizing Support Vector Machine (SVM). This algorithm was chosen because it performs well on text data with a very large number of features, such as comments containing religious responses and ethical issues in the digital space. The robust nature of SVM towards complex data is an important reason, especially since the use of TF-IDF will generate a high number of features that tend to be sparse. Several previous studies also indicate that SVM is quite consistent in sentiment analysis tasks in the Indonesian language, particularly when combined with TF-IDF representation, as demonstrated by [32] who found high performance when combining TF-IDF with SVM for opinion classification on social media.

Mathematically, SVM works by finding the optimal hyperplane that maximizes the margin between classes. The linear separating function in SVM can be written as:

$$(f(x) = w^T x + b) \tag{1}$$

with w as a weight vector, x as a representation of TF-IDF features, and as a bias. Comments are classified based on the sign of the following decision function:

$$(y = \text{sign}(w^T x + b)) \tag{2}$$

In preaching commentary, one often encounters various meanings, such as expressions of prayers or spiritual statements that are not always clearly separated. Therefore, SVM utilizes slack variables to assist data that is difficult to separate perfectly. The optimization process is governed by the objective function:

$$(\min_{w,b,\xi} \quad \frac{1}{2}|w|^2 + C\sum_{i=1}^{n} \xi_i) \tag{3}$$

With limitations:

$$(y_i(w^T x_i + b) \geq 1 - \xi_i,\ \xi_i \geq 0) \tag{4}$$

The parameter C plays an important role in balancing between a wide margin and tolerance for classification errors. In certain cases, SVM also utilizes a kernel function to map data into a higher-dimensional space so that the hyperplane can be found more effectively. The formulation of the decision function in the kernel trick is expressed as:

$$(f(x) = \text{sign}(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b)) \tag{5}$$

with as a Lagrange multiplier and as a kernel function. Once the model is defined, the processed data is split using the train-test split method to separate the training and testing phases. This step is used to evaluate how well the model handles new data it has not encountered during the learning process. This approach is similar to that used by [33] in digital application sentiment analysis and has been shown to help improve the objectivity of model generalization evaluation.

The model development phase is reinforced with verification to determine the optimal hyperparameter values, such as the parameter C and the type of kernel. This stage helps ensure that the model can perform well on new data and is not overly tied to patterns that appear from only a small portion of the data. Through this checking, the performance of the SVM becomes more consistent in classifying comments containing various religious expressions, moral appeals, and other ethical responses, which are usually written in different linguistic styles and contexts in the digital preaching space on YouTube.

2.5 Evaluation Model

Performance models are evaluated using accuracy, precision, recall, and F1-score to provide a more comprehensive understanding of the capabilities of its classification. Accuracy reflects the extent to which the model makes the exact prediction overall. Precision assesses how accurate models when recognizing a type of sentiment. Recall measures the ability of the model in identifying all relevant data in each category. Meanwhile, F1-Score serves as a measure of balance between precision and recall, especially when data is not balanced or has many variations of meaning, such as da'wah comments containing spiritual messages, moral values, or other religious response. The fourth use of this metric simultaneously contributes to a more comprehensive evaluation related to the performance of SVM in analyzing sentiments related to digital ethics in the da'wah video comment column on YouTube.

IV. RESULTS AND DISCUSSIONS

This stage presents the results of applying and evaluating the Support Vector Machine (SVM) model to analyze sentiment in comments on Islamic preaching videos on YouTube. The collected comments were processed through several preprocessing steps, including text cleaning, normalization, tokenization, stopword removal, and stemming. These steps were conducted to reduce noise, remove irrelevant symbols, and standardize linguistic variations commonly found in user-generated religious content, such as informal spelling, repeated characters, and mixed language usage. Through this preprocessing phase, raw textual comments were transformed into structured textual data that are suitable for computational sentiment classification and further analysis. The preprocessed data were subsequently transformed into numerical features using the Term Frequency–Inverse Document Frequency (TF-IDF) representation. This approach assigns weights to words based on their frequency and relevance within the corpus, allowing the model to capture meaningful patterns while minimizing the influence of commonly occurring but less informative terms. Comments labeled into positive, neutral, and negative sentiment categories were then analyzed to examine their overall sentiment distribution, which is visualized in graphical form in Figure 3.

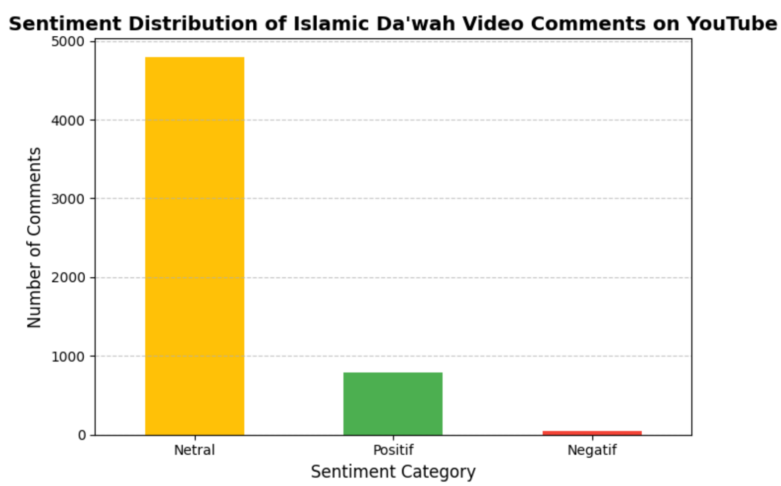

Figure 3. *Distribution of Sentiment Categories in YouTube Islamic Preaching Comments*

The visualization reveals a clear dominance of the neutral sentiment class, followed by the positive class, while the negative class appears with a considerably lower frequency. This distribution reflects the natural characteristics of audience responses to Islamic preaching content, where comments are often expressed in a calm, respectful, and informational manner rather than through strong emotional expressions. Many responses consist of short affirmations, prayers, acknowledgments, or descriptive statements that do not explicitly convey emotional polarity. Presenting the data graphically facilitates a clearer understanding of sentiment distribution and provides a realistic depiction of audience interaction patterns within the analyzed dataset, while also serving as a contextual foundation for evaluating the performance of the SVM classification model.

The dominance of the neutral class indicates that comments on Islamic preaching content are generally expressed in the form of informative statements, short prayers, or affirmative expressions that do not convey strong emotional intensity. This pattern explains why the SVM model demonstrates its best performance in the neutral category compared to the other sentiment classes.

The prevalence of neutral expressions reflects the communicative style commonly found in religious discourse, where users tend to respond politely and descriptively rather than emotionally. For the modeling stage, TF-IDF representation was employed to extract textual features, which were subsequently processed using the Support Vector Machine (SVM) algorithm. The performance of the classification model was evaluated using a test dataset, and the results are summarized in Table 1. The table presents precision, recall, F1-score, and support values for each sentiment category.

Tabel 1. SVM Model Evaluation Results

Kelas	***Precision***	***Recall***	***F1-Score***	***Support***
Negatif	1.00	0.08	0.15	12
Netral	0.97	1.00	0.99	965
Positif	1.00	0.89	0.94	150
Accuracy	-	-	0.98	1127
Macro Avg	0.99	0.66	0.69	1127
Weighted avg	0.98	0.98	0.97	1127

Based on the results shown in Table 1, the SVM model achieved an overall accuracy of approximately 98%, with the strongest performance observed in the neutral class. The high recall value for the neutral category indicates that the model consistently and accurately identifies neutral comments. In contrast, the recall values for the positive and negative classes are relatively lower. This performance gap can be attributed to class imbalance within the dataset, as well as semantic similarities between positive or negative comments and neutral, descriptive statements commonly used in religious discourse. The confusion matrix results are presented in tabular form to provide a clearer, more compact, and more interpretable representation of the classification errors produced by the Support Vector Machine (SVM) model. Unlike graphical visualization, a tabular confusion matrix allows readers to directly observe the relationship between actual sentiment labels and the predicted categories generated by the model. This format is particularly suitable for journal publication, as it presents numerical evidence of classification performance in a precise and concise manner. The distribution of predicted versus actual sentiment categories is summarized in Table 2, which replaces the graphical confusion matrix and enables a detailed examination of misclassification patterns across sentiment classes. By presenting the confusion matrix in tabular form, it becomes easier to identify which sentiment categories are correctly classified and which categories tend to be confused by the model.

Furthermore, the tabular confusion matrix provides insight into how the dominance of certain sentiment categories influences model behavior. In datasets where class imbalance is present, such as in religious discourse where neutral expressions are prevalent, a tabular confusion matrix helps explain why certain classes achieve higher recall while others experience more frequent misclassification. Therefore, Table 2 serves as an important complement to the overall performance evaluation by illustrating the practical implications of sentiment distribution and linguistic characteristics within the dataset.

Table 2. Confusion Matrix of SVM Sentiment Classification

Actual \ Predicted	Negative	Neutral	Positive	Total
Negative	1	11	0	12
Neutral	0	965	0	965
Positive	0	17	133	150
Total	1	993	133	1127

Table 2 presents the confusion matrix of the SVM sentiment classification results, comparing the actual sentiment labels with the predicted categories generated by the model. The table shows that the neutral sentiment class achieves the highest classification performance, as all 965 neutral comments are correctly predicted as neutral. This result indicates that the model performs very well in recognizing the dominant sentiment category within the dataset. For the negative sentiment class, only 1 out of 12 comments is correctly classified as negative, while 11 negative comments are misclassified as neutral. This low recall value reflects the difficulty of identifying negative sentiment in religious discourse, where criticism or disagreement is often expressed indirectly and without explicit emotional cues. The very small number of negative samples further contributes to this limitation.

In the positive sentiment class, 133 out of 150 comments are correctly classified as positive, while 17 positive comments are misclassified as neutral. This indicates that although the model performs relatively well in identifying positive sentiment, some positive expressions overlap semantically with neutral statements, particularly when appreciation or affirmation is conveyed in a subtle and descriptive manner.

Overall, the confusion matrix reveals that most classification errors occur when positive and negative comments are predicted as neutral rather than being confused with each other. This pattern suggests that the SVM model tends to favor the neutral category, which is consistent with the linguistic characteristics of Islamic preaching comments that emphasize politeness, moderation, and indirect expression.

To further explain this classification tendency, the overall distribution of sentiment classes in the dataset is presented in Table 3.

Table 3. Sentiment Distribution of YouTube Comments

Sentiment Class	Number of Comments	Percentage (%)
Positive	150	13.31
Neutral	965	85.67
Negative	12	1.02
Total	**1127**	**100.00**

Table 3 shows that neutral sentiment overwhelmingly dominates the dataset, followed by positive sentiment, while negative sentiment appears in a very small proportion. This imbalance explains the high recall achieved for the neutral class and the frequent misclassification of minority classes as neutral, as observed in the confusion matrix results. The dominance of neutral expressions indicates that user responses to Islamic preaching videos are generally conveyed through informative statements, short prayers, and polite affirmations rather than explicit emotional expressions. Such patterns suggest that audience engagement in digital da'wah contexts tends to prioritize information sharing and spiritual acknowledgment over emotional debate. This communication tendency reflects the values of moderation, respect, and social harmony that characterize ethical interaction in Islamic discourse. To complement the quantitative findings and to provide deeper qualitative insight into how each sentiment category is manifested in actual user responses, representative examples of comments for positive, neutral, and negative sentiment classes are presented in Table 4.

Table 4. Examples of Classified Comments

Sentiment Class	Example Comments
Positive	"May Allah bless the preacher and grant him health and wisdom." "Thank you for the enlightening lecture, it is very beneficial." "This sermon is very inspiring and calming for the heart." "May Allah reward the preacher for sharing valuable knowledge." "The explanation is clear and delivered with great wisdom."
Neutral	"This lecture is broadcast every Tuesday night." "The video duration is about one hour." "I often watch this channel for religious content." "The preacher explains the topic step by step." "This lecture discusses daily religious practices."
Negative	"I do not fully agree with this explanation." "Some parts of the lecture are confusing." "This topic needs further clarification." "The explanation feels incomplete." "I have a different understanding regarding this issue."

V. CONCLUSIONS AND RECOMMENDATIONS

This study analyzed sentiment in user comments on Islamic preaching videos on YouTube using a Support Vector Machine (SVM) model with TF-IDF feature representation to evaluate patterns of digital ethics in online religious discourse. The results show that neutral sentiment dominates the dataset, accounting for 85.67% (965 out of 5000 comments), followed by positive sentiment at 13.31% (150 comments), while negative sentiment appears only at 1.02% (12 comments). This distribution indicates that the majority of user interactions are expressed in a neutral and descriptive manner, reflecting restrained and polite communication behavior in digital Islamic preaching contexts.

The performance evaluation demonstrates that the SVM model achieved an overall accuracy of approximately 98%, with the best performance observed in the neutral sentiment class. The neutral class obtained a recall value of 1.00, indicating that all neutral comments were correctly identified by the model. In contrast, the positive sentiment class achieved a recall of 0.89, while the negative sentiment class showed a very low recall of 0.08, mainly due to the extremely small number of negative samples and the semantic overlap between mildly negative expressions and neutral statements.

The confusion matrix analysis further confirms that most misclassifications occur when positive (11.33%) and negative (91.67%) comments are predicted as neutral, rather than being confused with each other. This pattern highlights the impact of class imbalance and the linguistic characteristics of religious discourse, where emotional expressions are often conveyed indirectly through polite, moral, or spiritual language. From a digital ethics perspective, the findings indicate that YouTube comment sections related to Islamic preaching largely function as ethically moderated digital spaces. With more than 98% of comments classified as neutral or positive, user interactions generally reflect respectful communication, moral restraint, and social harmony in line with Islamic ethical values. The very small proportion of negative sentiment suggests that disagreement or criticism is typically expressed in a mild and non-confrontational manner.

Based on these results, this study concludes that SVM-based sentiment analysis is effective for identifying dominant interaction patterns and assessing digital ethics in online Islamic preaching environments. However, to improve the detection of minority sentiment classes, future research is recommended to balance sentiment distributions, increase dataset size, and incorporate semantic or context-aware features. Practically, these findings may serve as a reference for religious content creators and platform stakeholders to maintain and promote ethical communication practices within digital religious communities.

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