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Research Article

Multimodal Sentiment Analysis in Indonesian: A Comparative Study of Deep Learning Models for Hate Speech Detection on Social Media

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Abstract

With the rapid expansion of social media, the prevalence of hate speech has become a critical issue, particularly in the context of Indonesian language and culture. The detection of hate speech in social media platforms is a complex task due to the multimodal nature of online communication, where text, images, and videos are often combined to express sentiments. This study aims to explore and compare deep learning models for multimodal sentiment analysis, focusing on their effectiveness in detecting hate speech in Indonesian social media content. By analyzing both textual and visual data, the study seeks to enhance the accuracy of sentiment classification, specifically identifying instances of hate speech. The research employs several state-of-the-art deep learning models, including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Transformer-based models, to perform sentiment analysis on a multimodal dataset. The dataset includes text and images from Indonesian social media posts, labeled for hate speech detection. The results show that multimodal models outperform text-only models, with the Transformer-based model yielding the highest accuracy and F1-score in detecting hate speech. The inclusion of visual data significantly improved the model's ability to classify complex and subtle expressions of hate speech.

Keywords: Deep Learning, Indonesian Language, Social Media.

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INTRODUCTION

In recent years, the rapid proliferation of social media platforms has given rise to a new wave of communication that combines various modalities, such as text, images, and videos (Lozano-Lozano dkk., 2020; Vargas & Magnussen, 2022). This shift has led to a more complex environment for understanding user sentiment, especially when it comes to harmful content like hate speech. Hate speech on social media has become an alarming issue, as it can contribute to violence, discrimination, and social unrest. Identifying hate speech is essential for maintaining a safe online environment, and doing so is particularly challenging in multilingual and culturally diverse contexts, such as Indonesia. The linguistic richness of the Indonesian language, combined with the multimodal nature of social media posts, makes the detection of hate speech a particularly difficult problem (Lalitha dkk., 2020; Moradi Abbasabady & Razeghi, 2024). Traditional sentiment analysis models, which rely solely on text, may not capture the nuances of hate speech, which can often be conveyed through images, memes, and videos alongside text.

Social media platforms have become breeding grounds for expressions of hate, often wrapped in indirect language or conveyed through multimodal means. With the increasing volume of user-generated content, automating the detection of harmful language has become critical. Recent advancements in deep learning, particularly in the areas of natural language processing (NLP) and computer vision, offer promising solutions to this issue (Lund, 2022; Triejunita dkk., 2021). The application of deep learning models to multimodal sentiment analysis allows for the combined interpretation of both textual and visual data, potentially increasing the accuracy of hate speech detection. This has sparked interest in applying deep learning models to identify hate speech across various platforms. However, studies that focus on Indonesian social media content, especially within the context of multimodal data, remain limited (Ditsche dkk., 2023; Sulla, 2021). This research explores the effectiveness of deep learning models, specifically for the Indonesian language, by evaluating their ability to detect hate speech using both textual and visual content.

Although significant progress has been made in hate speech detection, particularly using deep learning methods for text-based analysis, the incorporation of multimodal data (text, images, and videos) remains underexplored in the context of Indonesian social media (Carvalho dkk., 2021; Huang dkk., 2022). The challenge lies not only in detecting hate speech but also in dealing with the intricacies of language use in Indonesian, which can vary across regions, social groups, and contexts. Furthermore, social media users often combine text with images or memes to convey messages of hate, making detection even more complex. Standard text-based models struggle to capture these subtleties, and there is an increasing need to assess how visual content contributes to the expression of harmful speech.

Most research in sentiment analysis and hate speech detection has focused primarily on Western languages, particularly English, with much less attention given to low-resource languages like Indonesian. While there has been some progress in analyzing hate speech in text for Indonesian, the challenge of dealing with multimodal content, which blends text with images, has not been sufficiently addressed. This research aims to tackle this gap by applying and comparing various deep learning models for multimodal sentiment analysis specifically for Indonesian social media (Gallego-Lema dkk., 2020; Widiati dkk., 2021). The focus will be on evaluating the performance of these models in detecting hate speech that is conveyed through a combination of text and images, rather than relying on text alone. This study seeks to develop a robust model capable of understanding the intricate ways hate speech is expressed in Indonesian, which is crucial for improving online content moderation systems.

The primary objective of this study is to evaluate the effectiveness of different deep learning models in detecting hate speech on Indonesian social media using multimodal data. The research aims to assess how various models, such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and transformer-based models, perform when trained on both textual and visual content (Agrawal, 2023; Hakim dkk., 2024). Specifically, the study will compare the performance of text-only models with multimodal models that integrate both text and images. The goal is to identify which models perform best in detecting hate speech in Indonesian social media posts and to understand how well the combination of textual and visual data can improve detection accuracy.

This study also aims to investigate the role of contextual factors, such as the socio-cultural nuances in Indonesian, in shaping how hate speech is expressed (Choudhry dkk., 2021; Gudkova dkk., 2021). By focusing on multimodal inputs, the research will explore how the interaction between text and image influences the effectiveness of hate speech detection models. Another goal is to explore how deep learning techniques can be adapted to the specific challenges posed by Indonesian, such as its syntactic variations, colloquialisms, and cultural references. The research will evaluate the ability of these models to generalize across different types of social media content, including tweets, Facebook posts, and Instagram images, to provide insights into the scalability of multimodal models for hate speech detection in diverse online environments.

While several studies have explored the application of deep learning for text-based sentiment analysis and hate speech detection, there is a noticeable gap in research focusing on multimodal sentiment analysis for regional languages like Indonesian. Much of the existing literature on multimodal hate speech detection has concentrated on high-resource languages, such as English, where large, labeled datasets are available. In contrast, there is limited research on using multimodal approaches for detecting hate speech in Indonesian, a language with its own complexities, dialects, and variations (Choudhry dkk., 2021; Sozontova dkk., 2020). Furthermore, many studies in the domain of Indonesian sentiment analysis have focused primarily on text, neglecting the role of images and other visual elements, which are crucial in the online expression of hate speech.

This study addresses the gap by focusing on the unique challenges posed by multimodal content on Indonesian social media (Cuesta & Alda, 2021; Nugraha dkk., 2021). While there has been some work in the realm of Indonesian language processing, the application of multimodal deep learning models to analyze both text and images for hate speech detection is largely unexplored. The contribution of this research lies in the development and comparison of multiple deep learning models tailored for multimodal data, specifically targeting the nuances of the Indonesian language. The findings from this study will significantly enrich the field by offering insights into how multimodal data can be effectively utilized in the detection of hate speech in underrepresented languages (Alfaidi & Semwal, 2022; Sulla, 2021). Additionally, this research aims to provide a foundation for future work in multimodal sentiment analysis for languages beyond the dominant, high-resource languages.

The novelty of this research lies in its focus on applying multimodal deep learning models to the detection of hate speech in Indonesian social media content. While multimodal sentiment analysis has been explored in several languages, there is little research specifically addressing how such approaches can be adapted to Indonesian. By incorporating both text and visual elements into the sentiment analysis process, this study offers a unique perspective on how deep learning models can enhance the detection of hate speech in a linguistically and culturally diverse context (Cuesta & Alda, 2021; Hamzah dkk., 2021). The research also contributes to the broader field of natural language processing by developing a robust model tailored to the unique challenges posed by Indonesian, such as its complex syntax, rich colloquialism, and sociolinguistic variations across different regions and social groups.

The justification for this study is rooted in the increasing importance of addressing hate speech in online platforms, especially in diverse linguistic and cultural contexts like Indonesia. The use of natural language-based models for detecting hate speech has proven to be effective in high-resource languages, but extending these models to Indonesian, with its unique linguistic structure and multimodal expressions of hate, is an essential step in improving content moderation across platforms in Indonesia. The findings of this research will not only contribute to the development of more efficient and accurate hate speech detection systems but also advance the understanding of how multimodal inputs can improve sentiment analysis in languages with limited resources and unique characteristics (D'Aniello dkk., 2020; Jones dkk., 2022). This research is crucial for fostering safer and more inclusive online spaces in Indonesia, with broader implications for content moderation in other multilingual settings.

RESEARCH METHOD

The research design for this study follows a comparative approach, aiming to evaluate and compare the effectiveness of various deep learning models in performing multimodal sentiment analysis for hate speech detection on Indonesian social media. This study integrates both textual and visual data to analyze sentiment, focusing on detecting hate speech through a combination of text and images (Kimura dkk., 2023; Sanchez-Martinez dkk., 2024). The models will be compared based on their ability to accurately identify hate speech, considering various metrics such as accuracy, precision, recall, and F1-score. The comparison will include text-only models as a baseline and multimodal models that integrate both text and visual data to determine the impact of multimodal input on detection performance.

The population for this study consists of publicly available social media posts in the Indonesian language, specifically from platforms such as Twitter, Facebook, and Instagram (Chu dkk., 2024; Shieh & Hsieh, 2021). The sample includes 10,000 posts, with an equal distribution of hate speech and non-hate speech content, ensuring that the dataset represents a variety of social media interactions. Posts will be selected to include both textual content (tweets, captions) and visual content (images, memes) that may contain hate speech elements. These posts will be labeled based on the presence or absence of hate speech, as defined by established hate speech guidelines, and then preprocessed for use in the analysis (Ahangarzadeh dkk., 2024; Butt dkk., 2020). The samples will include diverse topics, such as political discourse, social issues, and identity-related content, to capture the broad spectrum of hate speech on Indonesian social media.

The primary instruments for this study are deep learning models for sentiment analysis, including convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and transformer-based models like BERT and its variants. For the multimodal models, both text and image features will be extracted from the posts, with the text being processed using tokenization, embedding layers, and sequence models. Images will be processed through CNN architectures that focus on feature extraction. Both text and image data will be combined in a multimodal approach, where the textual and visual features are integrated into a unified representation before being fed into the deep learning models (Mochalina dkk., 2020; Subudhi R.N. dkk., 2022). Additionally, pre-trained models such as BERT for text and ResNet for images will be fine-tuned to optimize performance for the hate speech detection task. The models will be evaluated using performance metrics such as accuracy, precision, recall, and F1-score.

The procedures for data collection begin with scraping social media posts from the selected platforms (Helmold, 2021; Nordhagen dkk., 2023). The posts will be manually labeled as either containing hate speech or not, following predefined criteria for hate speech in Indonesian. After data collection, text preprocessing will be carried out, including removing irrelevant content, normalizing text, and tokenizing sentences. For image data, preprocessing steps include resizing images, normalizing pixel values, and extracting relevant visual features. The deep learning models will then be trained on the processed data, with separate models for text-only analysis and multimodal analysis. Training will involve optimizing the models through backpropagation using a standard optimizer such as Adam, with validation performed on a separate validation set (Nordhagen dkk., 2023; Subramaniam dkk., 2021). After training, the models will be tested on the held-out test set, and results will be analyzed to determine the effectiveness of multimodal approaches in detecting hate speech in Indonesian social media.

RESULTS AND DISCUSSION

The dataset used in this study consists of 10,000 Indonesian social media posts collected from Twitter, Facebook, and Instagram. These posts were labeled into two categories: hate speech (5,000 posts) and non-hate speech (5,000 posts). The dataset includes both text and images, with 50% of posts containing text-only content and the other 50% incorporating images alongside text (memes, photos, etc.). The total word count across all posts is approximately 1.2 million words, and the average number of words per post is 120. The images are approximately 200x200 pixels, ensuring uniformity in size for processing by convolutional neural networks (CNN). The data was preprocessed to remove irrelevant metadata and noise, with textual content tokenized and images normalized to fit the neural network input requirements.

Table 1. The dataset composition

Platform	**Total Posts**	**Text-Only Posts**	**Posts with Text & Image**	**Hate Speech Posts**	**Non-Hate Speech Posts**
Twitter	4,000	2,000	2,000	2,000	2,000
Facebook	3,000	1,500	1,500	1,500	1,500
Instagram	3,000	1,500	1,500	1,500	1,500

The dataset shows a balanced distribution of hate speech and non-hate speech content across different social media platforms. This balance ensures that the training process does not suffer from bias, which could otherwise affect the performance of the deep learning models. The inclusion of text-only posts and those with accompanying images allows for a more comprehensive evaluation of multimodal sentiment analysis. Given that hate speech often transcends mere words and can be expressed more implicitly through images, the inclusion of images alongside text is crucial for assessing the full range of multimodal hate speech. The dataset's structure enables the testing of the models across varying complexity, from simple text-based hate speech to more nuanced multimodal hate speech that combines visual and textual elements.

The balanced dataset is essential for the model's generalization, ensuring that both text and multimodal data types are effectively represented. By including memes and image-based content, which is common in online hate speech, the study examines how models perform in processing not just linguistic features but also visual cues that often play a critical role in expressing harmful or hateful sentiments. The varied composition of the dataset also reflects the diversity of social media usage, making the results applicable to a broader range of online platforms and scenarios.

The performance of the deep learning models was evaluated based on standard metrics such as accuracy, precision, recall, and F1-score. The text-only models achieved an average accuracy of 79.2% for detecting hate speech, while multimodal models that integrated both text and images performed better with an accuracy of 84.5%. The precision for hate speech detection in text-only models was 0.76, and recall was 0.78, whereas the multimodal models improved this to a precision of 0.81 and recall of 0.83. The results clearly demonstrate the advantage of incorporating visual data alongside textual content when performing sentiment analysis for hate speech detection.

The improvements in accuracy and other metrics for multimodal models can be attributed to the integration of image data, which adds an additional layer of information that helps the model understand contextual meanings. In cases where the text alone might be ambiguous or subtle, images (e.g., memes or sarcastic visuals) provide a clearer signal of hate speech. These findings underscore the importance of multimodal learning, especially in social media platforms where users often rely on both text and images to convey messages, including harmful or discriminatory language.

Inferential statistical analysis revealed that the integration of image data significantly improved the models' ability to detect hate speech. A paired sample t-test showed a statistically significant difference in accuracy between text-only models and multimodal models ($p < 0.01$), with multimodal models performing better across all platforms. The improvement in recall and precision for multimodal models indicates that incorporating both text and visual data allows the model to identify hate speech more comprehensively. Regression analysis confirmed that the addition of image features accounted for approximately 6.7% of the variance in hate speech detection performance, further supporting the conclusion that visual data enhances detection accuracy.

Moreover, the inferential analysis showed that the type of social media platform had a minor influence on the model's performance, with Twitter-based posts showing slightly higher performance metrics compared to Facebook and Instagram. This might be attributed to the more text-heavy nature of Twitter posts, making them more easily processed by text-based models. The analysis also revealed that the complexity of the language used in social media posts, including the use of slang, abbreviations, and emojis, had a notable impact on the detection accuracy, which was better handled by multimodal models as they could rely on visual context to resolve ambiguities in text.

The relational data analysis showed a strong correlation between user engagement (likes, shares, comments) and the likelihood of hate speech being detected. Posts with higher engagement rates, especially those with shared images or videos, were more likely to contain hate speech. This finding suggests that content that garners more interaction and attention is more likely to be inflammatory or provocative, often including multimodal cues such as memes, sarcasm, or aggressive imagery. The analysis revealed that the multimodal model performed particularly well in detecting hate speech in posts with high engagement, likely because these posts combined both text and visual content to amplify the message.

Additionally, the data suggested that the presence of controversial topics in the posts, such as politics or religion, was positively correlated with the likelihood of hate speech being detected. The relationship between the complexity of content (text and images) and the likelihood of hate speech indicates that multimodal models can capture not only explicit hate speech but also more implicit forms, such as sarcasm, humor, or coded language that are often expressed through a combination of text and images. This finding highlights the need for sophisticated models that can interpret both modalities effectively to detect the full range of hate speech present in online platforms.

A case study of a post from Twitter, which combined text and a meme featuring a political figure, illustrated the strength of the multimodal model. The text itself was relatively neutral, but the accompanying meme used exaggerated caricatures to imply harmful sentiments towards a specific ethnic group. The text-only model failed to detect hate speech, but the multimodal model accurately identified it by considering both the textual content and the visual cues in the meme. This case study highlights how hate speech can be subtle when relying on text alone but can be more easily identified when the model also considers the visual context.

Another case study from Instagram involved a post that used an image of a protest, combined with text that expressed inflammatory opinions about a religious group. In this case, the multimodal model was able to accurately classify the post as hate speech by incorporating the visual content of the protest, which added context to the text. The text-only model struggled to capture the full context, missing the inflammatory nature of the post. These case studies demonstrate how multimodal sentiment analysis can improve detection by combining multiple sources of information, making it particularly effective in platforms like Instagram and Twitter, where users commonly share multimodal content to convey messages.

Explanatory analysis of the results highlights the importance of integrating multimodal data to improve the detection of hate speech, especially in the Indonesian context, where users frequently employ both textual and visual cues in their online interactions. The effectiveness of multimodal models can be explained by the ability to process both the semantic meaning of the text and the visual context, which often provides additional layers of information that are crucial for understanding the intent behind a post. The ability to capture both forms of data allows for a more holistic understanding of online content, especially on platforms where images and memes are commonly used to amplify or distort messages.

Furthermore, the higher performance of the multimodal models also suggests that users expressing hate speech may rely on more complex forms of communication, combining both text and images to convey their message more forcefully. This behavior reflects a broader trend on social media, where content creators often use multimodal posts to grab attention and increase engagement. The model’s ability to process and analyze both elements simultaneously makes it more effective in detecting these forms of expression. The study suggests that for future work in hate speech detection, multimodal analysis should be a standard approach, especially in regions like Indonesia, where language use on social media is rich and diverse, incorporating both linguistic and cultural nuances.

In conclusion, the results suggest that multimodal deep learning models provide a significant advantage over text-only models in detecting hate speech on Indonesian social media. The ability to integrate both text and images allows for a more comprehensive analysis, improving detection accuracy and handling a broader range of expressions of hate speech. While text-based models performed adequately for straightforward cases, multimodal models excelled in more complex scenarios involving visual content. These findings highlight the importance of considering multimodal inputs in developing future sentiment analysis models, particularly in online environments where images and text are often combined to convey meaning.

This study explored the effectiveness of deep learning models for multimodal sentiment analysis in detecting hate speech in Indonesian social media posts. The results showed that multimodal models, which combined text and image data, outperformed text-only models in identifying hate speech. Specifically, the multimodal models achieved higher accuracy, precision, recall, and F1 scores compared to their text-only counterparts. The inclusion of image data, such as memes and visual cues, played a significant role in improving the model's ability to detect more subtle forms of hate speech that may not be fully conveyed through text alone. The study also revealed that while multimodal models performed well, the challenges of detecting hate speech in more ambiguous or context-dependent content remained, particularly for posts with complex language or mixed sentiment.

The results of this study align with previous research in the field of multimodal sentiment analysis, which has demonstrated the benefits of combining text and visual data for improved prediction accuracy (Kosti et al., 2017; Poria et al., 2017). However, this study expands on existing literature by focusing on Indonesian, a low-resource language with unique linguistic features and a rich cultural context. Previous studies on hate speech detection and multimodal sentiment analysis have primarily focused on English and other high-resource languages. In contrast, the application of these methods to Indonesian social media, with its own linguistic idiosyncrasies, presents new challenges and opportunities. This study contributes to the growing body of research on multimodal sentiment analysis by demonstrating that deep learning models can successfully address these challenges and improve hate speech detection in a diverse linguistic and cultural setting.

The results suggest that multimodal deep learning models are more effective in capturing the complexity of hate speech expressions, particularly in the diverse context of Indonesian social media. The ability to combine both text and visual data allows the model to better understand and interpret the contextual and emotional undertones of online content, which are crucial for detecting hate speech. The positive performance of multimodal models reinforces the importance of considering multiple sources of data in sentiment analysis, particularly when dealing with complex and culturally nuanced expressions of harmful speech. This finding signifies that for future hate speech detection tasks, integrating visual cues with textual content should be a standard practice, especially on platforms where images and text are commonly used together to convey powerful messages.

The implications of these findings are significant for the development of automated content moderation systems, particularly for platforms dealing with large amounts of user-generated content. The ability to accurately detect hate speech through multimodal models can help reduce the spread of harmful content, promote safer online environments, and facilitate more efficient content moderation. For businesses, government organizations, and social media platforms, these findings suggest the need to invest in more advanced multimodal AI systems to detect and manage hate speech in real-time. Additionally, these systems can be adapted to other languages and regions, making them a versatile tool for global applications in combating online hate speech. The study also provides a framework for future research on how multimodal deep learning models can be optimized for various languages and cultural contexts, especially those that are underrepresented in current AI research.

The results of this study can be attributed to the complex interplay between textual and visual information in online communication, particularly in the context of social media platforms like Instagram, Twitter, and Facebook. Text alone often fails to capture the full meaning of a post, especially when hate speech is expressed through subtle language or accompanied by strong visual cues. Memes, images, and other visual elements play a significant role in conveying the intended sentiment of the post, which text-only models cannot fully interpret. The multimodal models, however, were able to leverage both the text and image components to gain a more complete understanding of the post's content, leading to better identification of hate speech. This highlights the necessity of incorporating both modalities into the detection process, as relying on only one form of data leaves critical information unprocessed.

Future research should focus on refining multimodal models by incorporating additional modalities, such as audio or video, to further improve hate speech detection. Additionally, the performance of the models could be enhanced by using larger and more diverse datasets, including those from different regions of Indonesia, to ensure the model can generalize across various cultural contexts and dialects. Addressing the challenges of detecting more ambiguous or mixed-content posts will also be crucial for improving model accuracy. In addition, further work should explore how these models can be integrated into real-time content moderation systems to provide immediate, automated responses to harmful content. Lastly, the ethical considerations of using AI for content moderation must be addressed, ensuring that such systems respect free speech while effectively preventing the dissemination of hate speech. By taking these steps, the effectiveness and scalability of multimodal sentiment analysis models can be further expanded, benefiting online platforms, users, and society as a whole.

CONCLUSION

The most important finding of this study is the significant improvement in hate speech detection performance when using multimodal deep learning models compared to text-only models. The results demonstrated that multimodal models, which integrated both textual and visual data, achieved higher accuracy, precision, recall, and F1 scores in detecting hate speech across Indonesian social media platforms. This is especially relevant in the context of Indonesian social media, where hate speech is often expressed not just through text but also through images, memes, and visual symbols that carry contextual meaning. The inclusion of visual data allowed the models to better capture nuanced expressions of hate speech that would be missed by text-only models, showing the added value of incorporating multiple data types in sentiment analysis.

This research contributes significantly to the field of sentiment analysis by focusing on the integration of multimodal data in the detection of hate speech in the Indonesian language, which has been relatively underexplored in existing literature. The study uses advanced deep learning techniques to fuse text and image features, providing a more comprehensive approach to analyzing online content. The value of this study lies in its comparative evaluation of different deep learning models, including CNNs, LSTMs, and transformer-based models, and their application to low-resource languages like Indonesian. The findings demonstrate that multimodal deep learning models can be adapted to the unique linguistic and cultural characteristics of Indonesian, offering an innovative framework for future research in hate speech detection.

A limitation of this research is the dataset's reliance on only a few social media platforms (Twitter, Facebook, and Instagram) and the focus on hate speech related to specific domains such as political discourse. This may limit the generalizability of the findings to other social media platforms or broader categories of harmful content. Further research should focus on expanding the dataset to include a wider variety of social media platforms, particularly those popular in Indonesia but less explored in the context of sentiment analysis. Additionally, the current study does not address the challenge of detecting more subtle forms of hate speech, such as coded language or indirect expressions. Future studies could explore these aspects by incorporating more sophisticated techniques for identifying hidden hate speech or cross-cultural differences in how hate speech is expressed online.

Future research should focus on refining the multimodal models by expanding the dataset to include more diverse forms of online communication, such as video and audio content, which are increasingly common on social media. Additionally, exploring the use of transfer learning with multilingual datasets could help enhance the model’s ability to generalize across different languages and cultural contexts. Further, the effectiveness of these models in real-time hate speech detection systems needs to be tested, especially in the context of automated content moderation. As the ethical implications of using AI for content moderation continue to evolve, future work should also examine the potential biases in multimodal sentiment analysis models, ensuring that these systems are fair, transparent, and accountable while effectively combating harmful content online.

AUTHOR CONTRIBUTIONS

Look this example below:

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.
Author 4: Formal analysis; Methodology; Writing - original draft.
Author 5: Supervision; Validation.

CONFLICTS OF INTEREST

The authors declare no conflict of interest

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