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Classification of Political Party Conflicts and Their Mediation Using Modified Recurrent Convolutional Neural Network

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Abstract

The rapid proliferation of political information on the internet has exacerbated conflicts within political parties, including elite disputes, dualism, candidate controversies, and management issues, which can undermine political stability and public trust. To address these challenges, this study introduces the Modified Recurrent Convolutional Neural Network (M-RCNN), an enhanced RCNN model designed to improve classification accuracy and mitigate overfitting by incorporating additional layers and dropout mechanisms. The primary objective of this research is to provide an efficient and accurate framework for classifying political conflicts and mediation strategies, overcoming the limitations of traditional methods, particularly in handling imbalanced datasets and intricate data patterns. Using a dataset of 1,106 Indonesian news articles categorized into four conflict types—elite disputes, management, presidential, and legislative candidate conflicts—and four mediation strategies—leadership decisions, deliberation, legal channels, and none—the data underwent extensive preprocessing, tokenization, and an 80:20 training-testing split. The M-RCNN achieved a conflict classification accuracy of 98.0%, a precision of 99.0%, and a loss of 0.03, significantly outperforming baseline models, including CNN (85.0% accuracy), RNN with LSTM (88.0%), and standard RCNN (85.0%). For mediation strategy classification, the model demonstrated exceptional performance with an accuracy of 99.0%, a precision of 99.0%, and a loss of 0.01, highlighting its robustness and scalability. This study's novelty lies in its ability to process imbalanced and complex datasets with unparalleled precision and efficiency, providing a practical framework for automated political conflict analysis and mediation. The findings underline the potential of the M-RCNN model to revolutionize political science applications by delivering reliable, fast, and accurate tools for analyzing and resolving political conflicts, thereby contributing to the advancement of artificial intelligence in promoting political stability and fostering public trust.

Keywords: RCNN, Political Parties, Text Classification, Conflict Mediation, NLP, Deep Learning, Modified RCNN

1. Introduction

The diversity of Indonesia is closely tied to various disciplines and socio-political systems, including political communication, which significantly impacts elections [1], [2]. One way this impact is felt is through the wide dissemination of political information via virtual media on the internet. The use of social media has proven to attract significant attention, enabling rapid dissemination of political information and fostering active political participation [3], [4]. However, with the widespread circulation of political information, conflicts within political parties have become inevitable. These conflicts, often spreading via social media, can damage the electability and image of political parties, contributing to community polarization through the spread of hate speech by political buzzers [5].

The advances in artificial intelligence (AI) provide opportunities to utilize deep learning techniques for analyzing political information to mitigate misinformation and misunderstanding. By leveraging deep learning, it becomes possible to predict the type of political conflict and its mediation strategies quickly, yielding more accurate and consistent results than manual analysis [6], [7]. Deep learning, particularly in political science, utilizes Natural

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Language Processing (NLP) to extract information and detect patterns from political texts, which is often applied in text classification tasks such as email filtering, sentiment analysis, and document categorization [8], [9]. Specifically, Recurrent Convolutional Neural Network (RCNN), a combination of Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN), has been recognized for its proficiency in handling such tasks. The application of RCNN, particularly with Long-Short Term Memory (LSTM) for sequential data processing, has shown success in tasks like fake news detection [10], [11]. However, there has been limited research on the use of RCNN in predicting the types of political conflicts and their mediation strategies, especially within the Indonesian context.

To address these gaps, this paper proposes the Modified Recurrent Convolutional Neural Network (M-RCNN), which integrates an additional RCNN layer and Dropout to enhance accuracy and reduce overfitting [12]. This model is expected to optimize the classification of political conflicts and mediation strategies, providing consistent and efficient results. Several studies have employed deep learning models in text classification tasks within the political domain. For example, text classification has been widely used for fake news detection [13], [14] and sentiment analysis in various contexts, including Indonesian political datasets [15], [16]. Sentiment analysis has also been employed to measure the electability of political figures based on public comments on social media [17]. The utilization of deep learning significantly improves the accuracy of these tasks by leveraging word embedding techniques, which capture semantic relationships between words [18].

Recent works have explored the application of RCNN in various fields. For instance, RCNN has been used for classifying traffic disaster texts with high accuracy, leveraging the BERT model for text conversion and RCNN as the classifier [19]. Studies have shown that the incorporation of multiple layers in RCNN models, such as LSTM or GRU layers, improves the accuracy of text classification tasks [20]. Additionally, the RCNN model has demonstrated robust performance across different datasets and tokenizers, yielding better results compared to other deep learning methods [21]. However, the methodology used, such as the word substitution rate, can significantly impact the model's accuracy [22].

Despite the extensive use of deep learning models in NLP and text classification, there is a lack of research utilizing RCNN to classify political conflict types and mediation strategies. This paper aims to bridge that gap by proposing an RCNN-based approach to contribute to the growing body of political analysis research using deep learning.

2. Related Works

In this section, we conduct a literature review on text classification using the RCNN model. We also review recent literature studies on text classification using RCNN in the case of conflict classification and political party mediation, specifically in Indonesia.

Text classification in a political section is frequently used to classify fake news [14] or in sentiment analysis [23]. Text classification was used in Indonesia to detect fake news using 200 Indonesian news datasets. However, it used Stochastic Gradient Descent (SGD), Naive Bayes, and Logistic Regression (LR) to compare the results [24], multilabel headline news classification using Word2vec and LSTM [25], and classifying clickbait text in news headlines using Word Embedding and LSTM [26]. However, sentiment analysis is often used to measure a political figure's probability based on social media comments in Indonesia [17]. This text classification capability can assist in various applications, particularly in politics, including classifying categories of political conflict and mediation.

Deep learning saves a substantial workforce and material resources, improving text classification accuracy [27]. One of the advantages of using deep learning is utilizing the word embedding feature, which shows that word embedding can measure word relativity by giving the distance between vectors and can be used with any word accurately [18], [21]. Also, the paper discussed using deep learning to represent and classify texts by input word vector to bidirectional cyclic and convolutional neural networks (BRCNN) with better performance than traditional methods [7]. Dropout layers have been widely recognized for their ability to enhance model performance by improving generalization, mitigating overfitting, and providing a principled way to represent model uncertainty. Incorporating dropout has been shown to reduce prediction errors and improve key evaluation metrics, such as the Mean Squared Error (MSE) and the R^2 Score, as demonstrated in prior work [28].

This research will use a modification of the RCNN model to overcome the problem. With the current capabilities of RCNN, it can solve the problem appropriately. This study proposed an algorithm and model for classifying Chinese traffic disaster texts according to their severity. It obtained the highest accuracy using the BERT model for converting text and RCNN as a fine-tuning classifier [19]. RCNN capabilities are also quite competitive in other studies by discussing text classification accuracy by incorporating multiple layers into the traditional RNN model. The f1-score was used to compare the efficacy of the RCNN+LSTM model to another model with an average for hybrid RNN with three LSTM layers, and two GRU layers obtained an accuracy of 0.74 compared to RCNN+LSTM with an accuracy of 0.69 [20]. Also, the RCNN performance is highly capable of being used with any dataset and tokenizer with good results compared to other deep learning methods [21]. However, specific methodologies can impact the model's accuracy, such as using a low word substitution rate [22].

With many papers and research applying deep learning models in NLP schema, especially in text classification, no research uses RCNN to classify categories of political conflict and mediation, even though many studies on text classification use deep learning as a base model. Using the RCNN model enables our research to concentrate on bridging the divide and contribute to developing deep learning-based political analysis research.

3. Methodology

3.1. Proposed Model

For the task of conflict text classification and political party mediation, we propose a Modified RCNN model. The architecture of the proposed model is depicted figure 1.

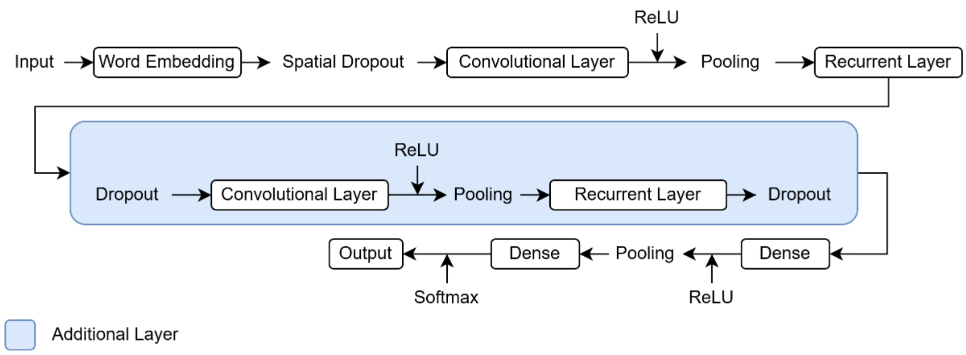

Figure 1. Proposed RCNN Model Architecture

The foundation of this model builds upon the original RCNN structure, which consists of an input layer followed by a word embedding layer, spatial dropout, a convolutional layer with ReLU activation, pooling, a recurrent layer, dense layers, and a softmax layer for classification. To enhance the model's performance and address limitations such as overfitting and insufficient feature extraction, modifications were introduced to the architecture. In the Modified RCNN, the input text is first processed by a word embedding layer, converting textual data into numerical representations suitable for neural network processing. Spatial dropout is applied to reduce spatial dependencies and improve generalization. A convolutional layer with ReLU activation is used to extract local features, followed by a pooling layer to reduce dimensionality and retain essential information.

To capture sequential patterns in the data, the model employs a Bidirectional LSTM (Bi-LSTM) layer as the recurrent layer, utilizing contextual information from both past and future states. To refine feature extraction further, an additional convolutional layer and pooling layer are introduced after the recurrent layer, followed by another Bi-LSTM layer to ensure deeper data representation, with dropout strategically applied after each recurrent layer to mitigate overfitting and enhance training efficiency. The processed features then pass through a dense layer with ReLU activation, followed by a Global Max Pooling operation to condense the features before reaching the output layer, which uses a softmax activation function to provide classification results. Key enhancements in the Modified RCNN include the incorporation of an additional convolutional and recurrent layer pair, along with dropout layers after each recurrent layer, improving the model's ability to capture complex features while ensuring robust generalization. The combination of ReLU and Softmax activations, dense connections, pooling mechanisms, and dropout layers enhances the overall efficiency and effectiveness of the architecture.

3.2. Dataset

The datasets used in this research were collected through web crawling from several Indonesian news portals, including Kompas, Detik, CNN Indonesia, Republika, and Tempo as well as data extracted from books and academic journals discussing political issues, and laws related to political parties, totaling 1106 pieces of Indonesian (Bahasa Indonesia) data, namely the Conflict Dataset and Mediation Dataset. The data was then categorized into four categories, including political elite conflicts, party management conflicts, presidential candidate support conflicts, and legislative candidate conflicts for Conflict Dataset, and four types, including leadership decisions, deliberation, legal channels, and none for Mediation Dataset, as shown in table 1 and table 2.

To evaluate the performance of the models, the dataset was split into three subsets: training, validation, and testing sets, with a ratio of 80:10:10, corresponding to 884 data points for training, 111 for validation, and 111 for testing. The splitting process was carried out randomly but consistently across all categories to ensure that data from all categories were represented in each subset. This approach was aimed at maintaining a fair and consistent evaluation of the models. Note that the amount of data in each category is unbalanced, which can affect the accuracy of the results of this research model. Despite this limitation, the splitting ratio was chosen to maximize the amount of data available for training while reserving sufficient data for unbiased validation and testing.

Table 1. Conflict Types Dataset

Table Head	Amount Data
Political Elite Conflict	580
Party Management Conflict	343
Presidential Candidate Support Conflict	124
Legislative Candidate Conflict	59
Total	1106

Table 2. Mediation Types Dataset

Mediation Labels	Amount Data
Deliberation	491
Leadership Decision	314
Legal Route	220
None	81
Total	1106

Before training, this dataset will process into training-ready data, referred to as pre-processing data. In this process, the data content of a dataset will be cleaned to produce data ready to be trained with a proficient level of accuracy. The first step is removing all punctuation marks from the dataset content to improve the text quality, as shown in table 3.

Table 3. Example of Removing Punctuation

Before	After
“Wakil Ketua Dewan Pembina Partai Solidaritas Indonesia (PSI) Grace Natalie mengatakan Sunny Tanuwidjaja mundur sebagai kader karena mendukung sosok Gubernur DKI Jakarta Anies Baswedan. Grace tak ingat pasti kapan Sunny menyampaikan itu. Grace hanya menyatakan bahwa Sunny sudah tak sejalan dengan sikap politik PSI. "Soal sudah atau akan (mendukung Anies) saya enggak ingat detail. Intinya begitu (Sunny mengaku dukung Anies)" kata Grace saat dihubungi Rabu (29/6). Ketua DPP PSI Isyana Bagoes Oka sebelumnya juga mengatakan hal serupa. Ia menyebut Sunny	“Wakil Ketua Dewan Pembina Partai Solidaritas Indonesia PSI Grace Natalie mengatakan Sunny Tanuwidjaja mundur sebagai kader karena mendukung sosok Gubernur DKI Jakarta Anies Baswedan Grace tak ingat pasti kapan Sunny menyampaikan itu Grace hanya menyatakan bahwa Sunny sudah tak sejalan dengan sikap politik PSI Soal sudah atau akan mendukung Anies saya enggak ingat detail Intinya begitu Sunny mengaku dukung Anies kata Grace saat dihubungi Rabu 296 Ketua DPP PSI Isyana Bagoes Oka sebelumnya juga mengatakan hal serupa Ia menyebut Sunny keluar dari PSI

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keluar dari PSI sejak tahun lalu. "Bro Sunny Tanuwidjaja telah mundur dari jabatan sebagai Sekretaris Dewan Pembina PSI sejak setahun lalu karena berbeda jalan politik" kata Isyana."	sejak tahun lalu Bro Sunny Tanuwidjaja telah mundur dari jabatan sebagai Sekretaris Dewan Pembina PSI sejak setahun lalu karena berbeda jalan politik kata Isyana"
"Deputy Chair of the Indonesian Solidarity Party (PSI) Board of Trustees Grace Natalie said Sunny Tanuwidjaja resigned as a cadre because he supported DKI Jakarta Governor Anies Baswedan. Grace does not remember exactly when Sunny said that. Grace only stated that Sunny was no longer in line with PSI's political stance. "Regarding whether he has or will (support Anies), I don't remember the details. The point is that (Sunny admitted to supporting Anies)," Grace said when contacted on Wednesday (6/29). PSI DPP Chair Isyana Bagoes Oka previously said the same thing. He said Sunny had left PSI since last year. "Bro Sunny Tanuwidjaja has resigned from his position as Secretary of the PSI Board of Trustees since last year because of different political paths," Isyana said."	"Deputy Chair of the Indonesian Solidarity Party PSI Board of Trustees Grace Natalie said Sunny Tanuwidjaja resigned as a cadre because he supported DKI Jakarta Governor Anies Baswedan Grace does not remember exactly when Sunny said that Grace only stated that Sunny was no longer in line with PSIs political stance Regarding whether he has or will support Anies I dont remember the details The point is that Sunny admitted to supporting Anies Grace said when contacted on Wednesday 629 PSI DPP Chair Isyana Bagoes Oka previously said the same thing He said Sunny had left PSI since last year Bro Sunny Tanuwidjaja has resigned from his position as Secretary of the PSI Board of Trustees since last year because of different political paths Isyana said"

It is followed by removing stop words and making all letters lowercase, intended not only to improve prediction accuracy and performance but also to speed up the training process of the proposed model, as shown in table 4. This process uses the library from NLTK and is specific to the Indonesian language.

Table 4. Example of Removing Stop Words and Lowercase Letters

Before	After
"Wakil Ketua Dewan Pembina Partai Solidaritas Indonesia PSI Grace Natalie mengatakan Sunny Tanuwidjaja mundur sebagai kader karena mendukung sosok Gubernur DKI Jakarta Anies Baswedan Grace tak ingat pasti kapan Sunny menyampaikan itu Grace hanya menyatakan bahwa Sunny sudah tak sejalan dengan sikap politik PSI Soal sudah atau akan mendukung Anies saya enggak ingat detail Intinya begitu Sunny mengaku dukung Anies kata Grace saat dihubungi Rabu 296 Ketua DPP PSI Isyana Bagoes Oka sebelumnya juga mengatakan hal serupa Ia menyebut Sunny keluar dari PSI sejak tahun lalu Bro Sunny Tanuwidjaja telah mundur dari jabatan sebagai Sekretaris Dewan Pembina PSI sejak setahun lalu karena berbeda jalan politik kata Isyana"	"wakil ketua dewan pembina partai solidaritas indonesia psi grace natalie sunny tanuwidjaja mundur kader mendukung sosok gubernur dki jakarta anies baswedan grace sunny grace sunny sejalan sikap politik psi mendukung anies detail intinya sunny mengaku dukung anies grace dihubungi rabu 296 ketua dpp psi isyana bagoes oka menyebut sunny psi bro sunny tanuwidjaja mundur jabatan sekretaris dewan pembina psi setahun berbeda jalan politik isyana"
"Deputy Chair of the Indonesian Solidarity Party PSI Board of Trustees Grace Natalie said Sunny Tanuwidjaja resigned as a cadre because he supported DKI Jakarta Governor Anies Baswedan Grace does not remember exactly when Sunny said that Grace only stated that Sunny was no longer in line with PSIs political stance Regarding whether he has or will support Anies I dont remember the details The point is that Sunny admitted to supporting Anies Grace said when contacted on Wednesday 629 PSI DPP Chair Isyana Bagoes Oka previously said the same thing He said Sunny had left PSI since last year Bro Sunny Tanuwidjaja has resigned from his position as Secretary of the PSI Board of Trustees since last year because of different political paths Isyana said"	"deputy chair indonesian solidarity party psi board trustees grace natalie sunny tanuwidjaja resigned cadre supported dki jakarta governor anies baswedan grace remember exactly sunny grace stated sunny longer line psis political stance regarding whether support anies remember details point sunny admitted supporting anies grace contacted wednesday 629 psi dpp chair isyana bagoes oka previously sunny left psi since bro sunny tanuwidjaja resigned position secretary psi board trustees since different political paths isyana"

The last step is tokenizing the data using the library from Keras word by word to be used later during the model training. This process converts a word into a unique number called a token, and each word has a different token. In this case, we get 17441 tokens in a dataset.

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4. Results and Discussion

The proposed model was compiled with a batch size of 64 and trained for 30 epochs using the Adam optimizer, with hyperparameters determined through empirical experimentation. Batch sizes between 32 and 128 were tested, and 64 was chosen as it provided a good balance between good result and more reliable [29]. The learning rate was dynamically adjusted using a learning rate scheduler, which reduced the rate when the monitored metric stopped improving, and an early stopping function was used to halt training when no further improvement was observed in validation loss, preventing overfitting. The Adam optimizer was chosen after comparing its performance to alternatives such as SGD and RMSprop, as it provided improved the accuracy in training, testing, and validation stages [30]. These tuning strategies ensured the model's optimal performance on both training and testing datasets. Additionally, the M-RCNN introduces enhancements over the standard RCNN, including improved feature extraction through additional layers, an attention-based mechanism to prioritize relevant features, and optimized training configurations for better convergence and performance. These modifications address the limitations of the base RCNN model, particularly in handling complex datasets like those used in this study.

All results show accuracy as a metric to evaluate the performance of the model, loss as a metric for the error between output and the actual output of the model, precision as a metric to evaluate the accuracy of optimistic predictions made by a model, recall as metric to evaluate the ability of the model to identify all relevant instances of the class, and f1-score as metric to evaluate the performance of model based on both precision and recall.

The proposed model performs satisfactorily and stops the training process at epoch 12 in classifying political party conflict types, compared to another model, RNN with LSTM stopped in epoch 5, GRU stopped in epoch 4, CNN in epoch 7, and RCNN in epoch 5, as shown in figure 2 and figure 3. The proposed model result also has better accuracy with obtained to 0.98 and a loss of 0.03 than other methods like RNN using LSTM with an accuracy of 0.88 and GRU of 0.79, CNN with an accuracy of 0.80, and the base RCNN model with an accuracy of 0.85, as shown in table 5.

In the testing period, the performance of proposed model obtained satisfactory results with a precision of 0.99, recall of 0.99, f1-score 0.99, and testing accuracy of 0.98, compared to RNN with LSTM, which only had a precision of 0.77, recall of 0.79, f1-score of 0.81, and testing accuracy of 0.80, RNN with GRU has a precision of 0.80, recall 0.82, f1-score of 0.78, and testing accuracy of 0.81, CNN has a precision of 0.87, recall 0.85, f1-score of 0.86, and testing accuracy of 0.84, and RCNN has a precision of 0.97, recall of 1.00, f1-score of 0.99, and testing accuracy of 0.80, as shown in table 6.

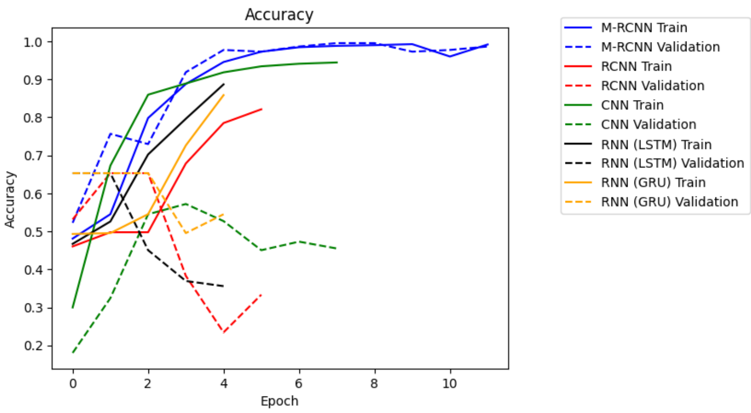

Figure 2. Comparison of Model Training Accuracy in the Classification of Political Party Conflict Types

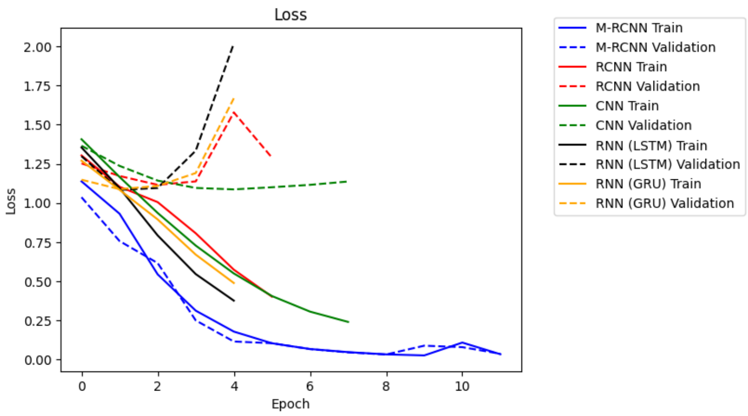

Figure 3. Comparison of Model Training Loss in the Classification of Political Party Conflict Types

Table 5. Mediation Types Dataset

Model	Accuracy
RNN (LSTM)	0.79
RNN (GRU)	0.81
CNN	0.85
RCNN	0.79
M-RCNN	0.98

Table 6. Mediation Types Dataset

Model	Precision	Recall	F1-Score	Accuracy
RNN (LSTM)	0.77	0.79	0.81	0.80
RNN (GRU)	0.80	0.82	0.78	0.81
CNN	0.87	0.85	0.86	0.84
RCNN	0.97	1.00	0.99	0.80
M-RCNN	0.99	0.99	0.99	0.98

Regarding political party conflict mediation results, the model training process runs the same compiler and callbacks but with different results. The M-RCNN outperformed the standard RCNN due to its modifications: improved feature extraction layers and training optimizations that allow the model to capture more relevant patterns in the mediation dataset. The proposed model stops the training process at epoch 19, compared to another model, RNN with LSTM stopped in epoch 4, GRU stopped in epoch 4, CNN in epoch 4, and RCNN in epoch 4, which can be said to have a considerable distance from the proposed model as shown in figure 2 and figure 3. This result also has significantly better accuracy than other methods, with an accuracy rate of 0.99. The RNN using LSTM have an accuracy of 0.61, GRU has an accuracy of 0.60, CNN has an accuracy of 0.50, and the RCNN has an accuracy of 0.56.

In the testing period, the performance of M-RCNN obtained satisfactory results with a precision of 1.00, recall of 1.00, f1-score of 1.00, and testing accuracy of 0.99, which is classified as almost accurate compared to RNN with LSTM, which only has a precision of 0.64, recall 0.56, f1-score 0.61, and testing accuracy of 0.60, RNN with GRU has a precision of 0.57, recall 0.54, f1-score 0.62, and testing accuracy of 0.63, CNN has a precision of 0.67, recall 0.53, f1-score 0.59, and testing accuracy of 0. 57, recall of 0.54, f1-score of 0.62, and testing accuracy of 0.63, CNN has a precision of 0.67, recall of 0.53, f1-score of 0.59, and testing accuracy of 0.59, and RCNN has a precision of 0.64, recall of 0.60, f1-score of 0.65, and testing accuracy of 0.45, which has a very far distance from the results of the proposed model.

The M-RCNN's accuracy and precision in classifying and mediating political conflicts provide policymakers with reliable data to proactively address issues and take preventive measures. This ultimately contributes to improved political stability and better public trust in decisions derived from data-driven insights [31].

5. Conclusion

The results of the proposed model show that the model has good accuracy in classification type of political party conflict and mediation in Indonesia by using datasets from Indonesian news articles compared to some deep learning models, with a value of 0.98 on conflict type classification and 0.99 on mediation. The results also prove that adding Dropout and additional RCNN layers reduces the risk of overfitting during the training process and reduces the loss in the model with a result of 0.10 in conflict type classification and 0.03 in mediation. With these results, the political section has the implication that will be applicated to analyze political information entirely fast and accurately by analyzing more than a thousand pieces of information every day and will add more types of political conflicts and mediations in the future, recommend using M-RCNN for the NLP task, and make the dataset balance for each class to get better and more accurate results.

6. Declarations

6.1. Author Contributions

Conceptualization: S.R., C.D., H.-C.C., R.A.-H.; Methodology: S.R., M.A.P.S., C.D.; Software: M.A.P.S., C.D.; Validation: S.R., M.A.P.S., C.D.; Formal Analysis: S.R., M.A.P.S., C.D., H.-C.C., R.A.-H.; Investigation: M.A.P.S., R.A.-H.; Resources: M.A.P.S., R.A.-H.; Data Curation: M.A.P.S., R.A.-H.; Writing Original Draft Preparation: S.R., M.A.P.S., C.D.; Writing Review and Editing: S.R., C.D., A.M.M.; Visualization: M.A.P.S., A.M.M.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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