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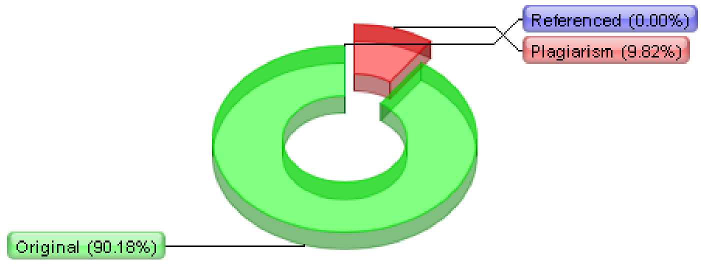

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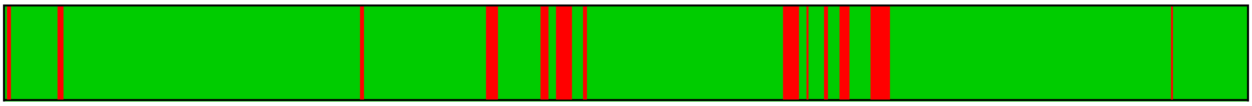

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On the Role of Text Preprocessing in BERT Embedding-based DNNs for Classifying Informal Texts Aliyah Kurniasih

Department of Computer Science University of Nusa Mandiri Jakarta, Indonesia Lindung Parningotan Manik Research Center for Data and Information Sciences National Research and Innovation Agency Cibinong, Indonesia Abstract-Due to highly unstructured and noisy data, analyz- ing society reports in written texts is very challenging. Classifying informal text data is still considered a difficult task in natural language processing since the texts could contain abbreviated words, repeating characters, typos, slang, et cetera. Therefore, text preprocessing is commonly performed to remove the noises and make the texts more structured. However, we argued that most tasks of preprocessing are no longer required if suitable word embeddings approach and deep neural network (DNN) ar- chitecture are correctly chosen. This study investigated the effects of text preprocessing in fine-tuning a pre-trained Bidirectional Encoder Representations from Transformers (BERT) model using various DNN architectures such as multilayer perceptron (MLP),

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long short-term memory (LSTM), bidirectional long-short term memory (Bi-LSTM), convolutional neural network (CNN), and gated recurrent unit (GRU

). Various experiments were conducted using numerous learning rates and batch sizes. As a result, text preprocessing had insignificant effects on most models such as LSTM, Bi-LSTM, and CNN. Moreover, the combination of BERT embeddings and CNN produced the best classification performance. Keywords-Natural language processing; bert embeddings; deep neural network; text preprocessing I. INTRODUCTION Societies often generate informal texts in the form of complaints, aspirations, and ideas. Therefore, it is crucial to follow up on most of the reports received by the various applications to increase service quality. However, the fluid, social, and dynamic written language that continues to develop becomes a challenge in natural language processing (NLP) research field. Furthermore, other challenges in text data such as typos, slang words, and informal vocabularies, followed by various hashtags and emoticons, remain to continue. In order to overcome these problems, text preprocessing is performed to manage text data before building an NLP model using machine learning. For example, removing hash- tags, URLs, stopwords, punctuations, @annotation, ASCII, and duplicate characters in a word is common in text mining [1]. Furthermore, tokenization, case-folding, stemming, and lemmatization were also performed preprocessing texts [2]. These steps are important in conventional machine learning since preprocessing can decrease vocabulary size by removing unhelpful parts of data or noise [3]. Thus, it can reduce the text data size and enhance the effectiveness and efficiency of the machine learning algorithms. However, these approaches could be problematic. Some preprocessing steps could make semantic meaning between tokens or words in sentences disappear. For example, remov- ing some stopwords could affect the contexts and generate ambiguous results. Sometimes, emoticons and hashtags could be helpful when analyzing emotions or sentiments within texts. Moreover, mistakes could be made if done manually or even automatically. To the best of our knowledge, no stemmer has 100% accuracy. Thus, in addition to losing the meaning, over stemming and under stemming could occur. There are several techniques for extracting text features. Within text mining, feature extraction means converting texts to vectors. In conventional machine learning, the Bag-of- Word (BOW) method and Term Frequency-Inverse Document Frequency (TF-IDF) are commonly used [4]. The deficiency of these approaches is that they do not capture the position in the text, co-occurrences in different documents, and the semantics. Some of these problems were solved with word embeddings, which are learned text representations in which words with related meanings are represented similarly. It is considered one of the breakthroughs in deep learning. Studies in [5], [6], [7] suggested the Word2Vec approach to extract text features, while others suggested Glove [8]. Nevertheless, both approaches are context-independent, and they could not catch all semantic information such as Out-Of-Vocabulary (OOV) and some opposite word pairs. Now-a- days, the NLP model that could perfectly capture almost all semantic contextual meanings is the Bidirectional Encoder from Transformers (BERT) [9]. It takes a sequence (typically a sentence) as input rather than a single word to generate contextual embeddings. Before BERT can build word embeddings, the context provided by surrounding words has to be shown. Word2Vec generates only one vector representation for each word. If there are any different word meanings, they are combined into one single vector. Meanwhile, BERT gener- ates different vectors of a single word in different contexts. It is a leap in text mining techniques where pre-trained models are utilized in transfer learning with Transformers network [10]. Some pre-trained BERT models are already available in some languages other than English, such as AnchiBERT for ancient Chinese language [11], PhoBERT for Vietnamese [12], and www.ijacsa.thesai.org 928 | P a g e IndoBERT for the Indonesian language [13], [14]. In previous studies, BERT has been applied in text classi- fication and generated passably result [15], [16], [17], [18], [19]. With many noises in the data, such as slang words, nonstandard abbreviations, and typos, experiments conducted in [20] to analyze the sentiments of flood disaster-related texts using a pre-trained BERT model showed promising results. The study claimed that the noises had great effects on accuracy. However, the authors did not experiment with text preprocessing to prove that claim. We hypothesized that choosing the suitable word embeddings approach and DNN architecture makes most text preprocessing steps no longer required. The contribution of this study is twofold. First, we investi- gated the effect of text preprocessing in the BERT embedding- based deep neural networks (DNNs) when classifying informal texts. While NLP studies suggested that text preprocessing was required most of the time, we argued that these tasks do not affect classification performance nowadays. Second, we also aimed to find and propose DNN architecture with the best classification performance in fine-tuning BERT embed- dings. Therefore, we conducted experiments with or without standard words based on Indonesian dictionary rules were done manually. Meanwhile, case-folding and removing numbers, mentions, hashtags, as well as emoticons were performed automatically. The IndoBERT model released by IndoNLU [13] was used to create the BERT embeddings of the dataset. The model was pre-trained using Masked Language Modelling (MLM) and Next Sentence Prediction (NSP), consisting of 124.5M parameters in the base architecture. A text data collection which consists of 4 billion words called Indo4B with a size of 23.43 GB, was used to train the model. Furthermore, we divided the dataset into 70% training data, 15% validation data, and 15% test data. Training data used to build model, validation data used to test the trained networks to validate model, and testing data used to test model that was built. Validation and test data used were not part of training data to produce an objective evaluation result. Moreover, five DNN architectures were trained. The LSTM, Bi-LSTM, CNN, MLP, and GRU were chosen since they performed well in previous studies [1], [8], [21]. TABLE II. HYPERPARAMETERS OF DNN ALGORITHMS most text preprocessing tasks using five DNN architectures, including

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long short-term memory (LSTM), bidirectional long short-term memory (Bi-LSTM), convolutional neural network (CNN

), multi-layer perceptron (MLP), and gated recurrent unit (GRU). In addition, each model was also tuned with various optimization methods and hyperparameters, such as learning rate and batch size. The remainder of this paper is organized as follows. First, Section II presents the dataset and research methods. Then, the results and discussions are explained in Section III and Section IV, respectively. Finally, conclusions and future research recommendations are provided in Section V. II. MATERIALS AND METHODS Parameter Parameter Value IndoBERT Indobenchmark/indobert-base-p1 Max length 512 Neuron 1024, 512, 256 Batch size 16, 32 Dropout 0.2 Activation function ReLu Output function Softmax Loss function Categorical crossentropy Epoch 20 Number of layer 1-5 Type of layer LSTM, BiLSTM, CNN, GRU, MLP Optimization Adam Learning rate 5x10-5, 3x10-5, 2x10-5 TABLE III. MODELS' ARCHITECTURE The research method in this study is shown in Fig. 1. First, we collected a dataset in the Indonesian language from society reports taken from a Citizen Relation Management Architecture Layer MLP One input layer, three dense layer (neuron 1024, 512, (CRM) application in the Water Resources Agency of Jakarta, Indonesia. There were 3,217 instances obtained from 1 Jan- LSTM 256), dropout layer (0.2), one output layer One input layer, one lstm layer (1024), two dense layer (512, 256), dropout layer (0.2), one output layer uary to 31 July 2021. Initially, the CRM administration staff BiLSTM One input layer, one bi-lstm layer (1024), two dense performed the manual classifications of the text reports into five handling categories, namely flood mitigation, waterways, drain closure, infiltration well, and others. The distribution of CNN layer (512, 256), dropout layer (0.2), one output layer One input layer, one convolutional layer (1024), one pooling layer, two dense layer (512, 256), dropout layer (0.2), one output layer data is displayed in Table I. TABLE I. NUMBER OF LABELED DATA Category Amount of Data Flood mitigation 1360 Waterways 1071 Others 423 Drain closure 343 Infiltration well 20 We performed text preprocessing semi-automatically be- fore conducting one of our sequences of experiments. Cor- recting abbreviated vocabulary, removing repeated syllable alphabet, repairing typos, and formalizing slang words to GRU One input layer, one gru layer (1024), two dense layer (512, 256), dropout layer (0.2), one output layer Hyperparameter values such as maximum length, the num- ber of neurons, learning rates, batch sizes, and epochs were determined based on previously conducted research related to BERT fine-tuning [15]. Moreover, the ReLu activation function was used on

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the hidden layer and the Softmax activation function on the output layer. The categorical cross-entropy was used as a loss function since target label classification has more than two classes. The dropout value was set to 0.2 used on the last hidden layer before the output layer

to regularize the model to decrease overfitting from happening on the model. Each model was built and experimented with a variation www.ijacsa.thesai.org 929 | P a g e Fig. 1. Research Method. amount of batch size of 16 as well as 32, learning rates of 5x10-5, 3x10-5, 2x10-5, and an epoch of 20. Moreover, Adam is used to optimizing the model since it is the best adaptive optimizer in most cases. The summary of the hyperparameter values is shown in Table II. Meanwhile, all DNN architectures were composed of one input layer, one output layer, and at least one hidden layer. The detail of the five architectures and the used parameters on the layers is represented in Table III. Standard performance metrics, such as TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative), were used as primary building blocks to evaluate classification models. A TP is measured

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when the model predicts the positive class correctly. A TN , on the other hand, is a result in which the model correctly classifies the negative class. Conversely, a FP occurs when the model predicts the positive class

inaccurately. Meanwhile, a FN is an outcome in which the model classifies the negative class inaccurately. Furthermore, other classification metrics, such as

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accuracy, F1-score, precision, and recall, were used to evaluate the mod- els' performances. The accuracy, calculated using Equation 1, is the ratio of the number of correct predictions divided by the total number of input samples. Meanwhile, recall, calculated using Equation 2, measures the model's ability to detect positive samples. On the other hand,

precision, calculated using Equation 3, measures the model's accuracy in classifying a sample as positive. Lastly, F1-score, which summarizes a model's predictive performance by combining two previously opposing variables -

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precision and recall, is calculated using Equation 4. F1-score could be considered the best metric in this study since

the dataset has an uneven class distribution. www.ijacsa.thesai.org 930 | P a g e TABLE IV. TEXT PREPROCESSING RESULTS Without Text Preprocessing With Text Preprocessing English Version mohon bantuannya got mampet, sudah saya bersihkan sebagian kotorannya tapi masih mam- pet dan sampai mengalir ke jalan #gotmampet #gotkotor jl Taman malaka selatan 3, duren sawit, jakarta timur laporan pak .di wilayah Cakung tepat nya di keluarahan rawa Terate kali sudah dangkal pak mohon untuk segera di keruk lumpur bir dlm.sudh mengadu ke lurah rawa Terate ttp blm ada tanggapan smpi skrng jln cipinang lontar rt13rw06 deket bekas hotel ahmad mas .. mohon solusi nya bapak ibu yg terhormat karena setiap hujan kami kebanjiran karena GOT yg susah untuk di bersihkan nya karena sebagian warga depan rumah nya itu di tinggikan di atas GOT @TMCPoldaMetro @RadioElshinta @DKI- Jakarta Kerusakan penutup gorong-gorong yang sama yang diperbaiki tgl 5 maret lalu. Jelek banget kualitasnya, bikin macet panjang di pertigaan Tipar Cakung - RGTC sampai 1 KM @DKIJakarta kok tidak ditindak lanjuti kerusakan penutup gorong-gorong ini? Pak, mohon dibuatkan sumur resapan disepan- jang jalan ini, selalu rawan banjirrrrrr mohon bantuannya got mampat, sudah saya bersihkan sebagian kotorannya tetapi masih mampat dan sampai mengalir ke jalan. jalan taman malaka selatan tiga duren sawit jakarta timur laporan pak, di wilayah cakung tepatnya di kelu- rahan rawa terate kali sudah dangkal pak. mo- hon untuk segera di keruk lumpur biar dalam. sudah mengadu ke lurah rawa terate tetap belum ada tanggapan sampai sekarang. jalan cipinang lontar rukun tetangga 013 rukun warga 006 dekat bekas hotel ahmad mas. mohon solusinya bapak ibu yang terhor- mat karena setiap hujan kami kebanjiran karena got yang susah untuk di bersihkannya karena sebagian warga depan rumahnya itu ditinggikan di atas got. kerusakan penutup gorong-gorong yang sama yang diperbaiki tanggal 5 maret lalu. jelek banget kualitasnya, bikin macet panjang di perti- gaan tipar cakung rgtc sampai satu kilometer, ko tidak ditindak lanjuti kerusakan penutup gorong- gorong ini? pak, mohon dibuatkan sumur resapan di sepan- jang jalan ini, selalu rawan banjir. please help the gutter is clogged, i have cleaned some of the dirt but it is still clogged and the water flows into the street street of south malaka park three duren sawit east jakarta sir, in the cakung area, to be precise, in the rawa terate sub-district, the river is already shallow. please immediately dredge the mud. i have com- plained to the village head, still no response until now cipinang lontar street, rt 013 rw 006 near the former hotel ahmad. please provide a solution, because every time it rains we are flooded. the sewers are difficult to clean because the front part of some of the residents' houses are elevated above the sewers. same damage to the culvert cover which was repaired on 5 march. very bad quality, causing a long traffic jam at the tipar cakung rgtc junction for up to one kilometer, how come no action is taken to fix the damage on this culvert cover? sir, please make an infiltration well along this road, it is always prone to flooding. Fig. 2. Representation of BERT Embeddings and CNN. www.ijacsa.thesai.org 931 | P a g e = TP + TN Accuracy = TP + TN + FP + FN TP Recall = TP + FN TP Precision = TP + FP F 1 score = 2 × precision × recall precision + recall (1) (2) (3) (4) accuracy, F1-score, precision, and recall were improved by 1.45%, 0.48%, 0.06%, and 1.59%, respectively. However, these values indicated that the text preprocessing made minimal performance improvements. Moreover, in order to make statistical comparisons of performance results of fine-tuned DNN model between with and without text preprocessing, the t-Test was performed. The statistic test can determine whether the differences between two approaches are significant. If the p-value is less than a significant level, the null hypothesis, which states no significant differences between the models, is rejected. The results are shown in Table VII, where p-values less than a significant level of 0.05, which indicated significant differences, are printed Finally, the performance results of DNN models with and without text processing were compared to see

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if there is a significant difference between both approaches using a statistical t-Test, Paired Two Sample for Means. The test statistic is calculated using Equation 5 where d¯ is the sample mean of the differences, s is the sample standard deviation of the differences, n is the sample size, and t is the Student t quantile with n-1 degrees of freedom

used to define the p- value. In statistical significance testing, it is the likelihood of receiving a test statistic at least as extreme as the observed one, assuming that

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the null hypothesis is true. The null hypothesis is rejected when the p-value is

smaller than the predetermined significance level, suggesting that the observed result would be highly implausible under the null hypothesis. d¯ t = s/ √ n (5) III. RESULTS Some of the results of text data after processing with and without text preprocessing used in building models

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are shown in Table IV. The performance results of various experiments without text preprocessing are shown in Table

V, where the highest values are printed bold. The fine-tuned DNN architec- ture with IndoBERT base model to text data of society reports without text preprocessing produced the best accuracy and precision using the CNN algorithm model architecture with

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a learning rate of 3x10-5 and a batch size of 16. The best accuracy and precision obtained were 83.85% and 88.76%, respectively. However, the best result on F1-score and recall was achieved using a learning rate of 5x10-5 and a batch size of

16. The best F1-score and recall yielded 85.44% and 83.95%, respectively. Meanwhile, the performance results of various experiments with text preprocessing are represented in Table VI, where the best values are boldly printed. The fine-tuned deep learning model with text preprocessing obtained the best accuracy, F1- score, and recall using the CNN algorithm with a learning rate of 5x10-5 and batch size of 16. The best

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accuracy, F1-score, and recall yielded 84.47%, 85.92%, and 85.54%, respectively. However, the best precision of 87.37% was produced using a learning rate of 2x10-5 and a batch size of 32. From the two tables, it can be seen that the CNN algorithm produced the best performances compared to other algorithms. CNN even produced better results using text preprocessing. With a learning rate of 5x10-5 and a batch size of 16, the bold. It can be seen that

text preprocessing had no significant effect on most architectures, such as in CNN, LSTM, and Bi-LSTM. Meanwhile, the text preprocessing significantly affected the performances of GRU as well as the accuracy and the precision of MLP but not the F1-score. IV. DISCUSSION The result of insignificant performance differences between DNN architectures with and without text preprocessing is in line with the study conducted by [22]. It performed various experiments with three preprocessing tasks: lowercasing, lem- matizing, and multiword grouping. It concluded that simple tokenization was generally adequate in DNN architectures, par- ticularly CNN. Furthermore, the simple preprocessing worked equally or better than more complex techniques in most cases, except for domain-specific texts, such as in the medical field, where apparent differences were needed to classify cardiovas- cular disease. We proved that the study conducted by [20] claimed that removing noises in the text data would significantly improve the accuracy of a pre-trained BERT model could be gone wrong. Instead, a BERT model applied to heavily cleaned text data could make things worse because the contextual information would be lost. This finding is supported by a study conducted by [23] when profiling authors from their writings. When no preprocessing method was used, the study found that BERT best predicted an author's gender. In the best scenario, the model was 86.67% accurate in estimating the writers' gender. One possible reason for the excellent performance of the model without text preprocessing in this study was the suitable choice of the word embeddings approach. The IndoBERT was trained on an extensive Indonesian text dataset that includes formal and slang language, such as tweets. The results could differ if the pre-trained BERT models were trained using Wikipedia corpus only, like the BERT-Base multilingual pre- trained model [16]. A study conducted in [19] showed that preprocessing steps and further preprocessing processes were needed when using BERT multilingual pre-trained model to improve the classification performance of a DNN. The more data BERT pre-train, the less the negative impact of misspellings and slang words would be because the model has more examples of typos, abbreviated vocabularies, ortho- graphic errors, et cetera. Furthermore, CNN managed to perform best when utilizing the BERT embeddings compared to the other DNN architec- www.ijacsa.thesai.org 932 | P a g e TABLE V. PERFORMANCE RESULTS OF MODELS WITHOUT TEXT PREPROCESSING Architecture Learning Rate Batch Size Accuracy (%) F1-Score (%) Precision (%) Recall (%) MLP 5x10-5 16 78.26 60.49 66.62 56.87 3x10-5 16 77.02 60.43 67.04 56.02 2x10-5 16 76.40 61.24 66.47 57.58 5x10-5 32 76.81 62.95 65.71 61.08 3x10-5 32 76.19 58.19 66.86 53.88 2x10-5 32 73.91 59.56 65.92 54.98 LSTM 5x10-5 16 69.98 54.17 54.93 54.09 3x10-5 16 72.26 65.14 77.95 61.06 2x10-5 16 69.36 52.68 57.14 50.20 5x10-5 32 72.67 55.91 58.63 54.20 3x10-5 32 72.26 56.38 57.16 55.87 2x10-5 32 71.01 53.07 55.30 51.40 BiLSTM 5x10-5 16 81.37 79.87 87.92 74.74 3x10-5 16 79.71 83.19 84.84 82.15 2x10-5 16 80.54 73.58 84.01 69.85 5x10-5 32 81.16 79.99 86.28 75.56 3x10-5 32 80.33 72.34 86.02 67.90 2x10-5 32 79.50 76.09 82.67 72.10 CNN 5x10-5 16 83.02 85.44 87.20 83.95 3x10-5 16 83.85 75.56 88.76 70.15 2x10-5 16 80.12 79.33 86.86 73.99 5x10-5 32 82.61 80.19 86.65 75.73 3x10-5 32 79.92 72.41 85.84 66.93 2x10-5 32 80.54 73.27 87.29 67.17 GRU 5x10-5 16 72.05 65.44 75.55 62.15 3x10-5 16 74.33 68.36 80.40 64.28 2x10-5 16 72.26 66.01 79.09 60.98 5x10-5 32 72.05 67.26 76.99 65.57 3x10-5 32 74.12 57.74 61.37 54.99 2x10-5 32 70.81 56.67 60.62 54.36 TABLE VI. PERFORMANCE RESULTS OF MODELS WITH TEXT PREPROCESSING Architecture Learning Rate Batch Size Accuracy (%) F1-Score (%) Precision (%) Recall (%) MLP 5x10-5 16 74.74 59.55 63.70 56.61 3x10-5 16 74.95 60.20 63.39 57.43 2x10-5 16 73.91 59.27 65.61 54.93 5x10-5 32 75.36 60.43 63.86 58.34 3x10-5 32 76.40 59.60 66.27 55.93 2x10-5 32 73.08 58.44 64.25 54.29 LSTM 5x10-5 16 68.32 51.08 53.48 50.20 3x10-5 16 73.50 57.67 59.59 56.18 2x10-5 16 70.19 54.02 57.58 52.07 5x10-5 32 69.98 61.68 79.68 55.77 3x10-5 32 71.22 55.08 57.27 54.62 2x10-5 32 68.32 52.42 54.58 50.74 BiLSTM 5x10-5 16 80.75 79.32 83.81 76.47 3x10-5 16 79.30 78.14 82.33 75.37 2x10-5 16 80.33 74 85.77 69.58 5x10-5 32 79.50 78.70 84.25 75.27 3x10-5 32 79.50 72.02 83.10 68.04 2x10-5 32 80.33 78.59 83.12 76.16 CNN 5x10-5 16 84.47 85.92 87.26 85.54 3x10-5 16 82.61 74.59 85.14 70.83 2x10-5 16 81.57 80.71 86.60 76.56 5x10-5 32 83.64 82.40 87.35 79 3x10-5 32 83.23 65.75 68.06 64.39 2x10-5 32 80.95 74.43 87.37 68.86 GRU 5x10-5 16 72.67 66.35 78.86 61.16 3x10-5 16 71.64 56.96 58.05 56 2x10-5 16 71.43 56.67 59.42 54.64 5x10-5 32 71.84 57.40 59.34 55.88 3x10-5 32 70.60 56.60 58.70 55.16 2x10-5 32 69.15 54.67 57.10 52.87 www.ijacsa.thesai.org 933 | P a g e TABLE VII. P-VALUES OF SIGNIFICANT TEST RESULTS Architecture Accuracy F1-Score Precision Recall MLP 0.0124 (sig.) 0.8727 (not sig.) 0.00519 (sig.) 0.29054 (not sig.) LSTM 0.10471 (not sig.) 0.31956 (not sig.) 0.48675 (not sig.) 0.16681 (not sig.) BiLSTM 0.10323 (not sig.) 0.25638 (not sig.) 0.10761 (not sig.) 0.43984 (not sig.) CNN 0.06955 (not sig.) 0.38748 (not sig.) 0.14476 (not sig.) 0.10301 (not sig.) GRU 0.04053 (sig.) 0.02643 (sig.) 0.03164 (sig.) 0.02431 (sig.) tures. It could be because the CNN algorithm might extract local and global features very well from the vectors using the convolutional, the pooling, and the fully connected (dense) layers, which can maintain semantic context meaning on text data. This finding supports studies on sentiment analysis of a commodity review and stance detection for credibility analysis of information on social media conducted by [24], [25]. These studies showed that BERT embeddings and CNN obtained better results than single CNN that ignores relation contextual semantics on text. BERT's input embeddings are composed of three differ- ent embeddings: Token Embeddings, Segment Embeddings, and Position Embeddings. Before being passed to the Token Embeddings layer, the input text is tokenized using

Plagiarism detected: **0.26%** https://iq.opengenus.org/embeddings-in-bert/ id: **13**

a method called WordPiece tokenization. It is a data-driven tokenization strategy that

balances vocabulary size and OOV words. Extra tokens are also added to the beginning and the end, namely the classification token ([CLS]) and the NSP token ([SEP]). These tokens have two functions: one serves as a representation input for classification tasks, and the other is to split a pair of input texts. Then, the sentence number is converted into a vector in Segment Embeddings. Meanwhile, the Position Embeddings create a vector for the word's position within the sentence. Finally, the three embeddings are summed up to generate a single shape representation passed to BERT's encoder layer [9]. Our proposed architecture is shown in Fig. 2. V. CONCLUSION This study showed that most text preprocessing tasks such as formalizing slang, fixing typos, case-folding, et cetera were not absolute things to do with transfer learning if the word embeddings method and DNN architecture were chosen correctly. There were insignificant differences between models with or without text preprocessing on most DNN architectures such as LSTM, Bi-LSTM, and CNN when utilizing BERT embeddings. Furthermore, combining BERT embeddings and CNN produced the best classification performance. Rather than wasting time preprocessing text data, researchers should focus on finding a suitable word embeddings approach and DNN architecture. Future studies should investigate the significance of each text preprocessing step since there were significant differences in performance results between the model with and without text preprocessing using GRU and MLP.