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Optimization of Nutrimax Food Supplement Rating Classification Using a Hybrid CNN-LSTM Approach

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Abstract
Nutrimax Food Supplement is a company specializing in the production of vitamins and pharmaceuticals, with a 4.9-star rating on the Shopee e-commerce platform. Product ratings and reviews play a crucial role in online purchasing decisions, as consumers often rely on previous buyers' experiences to mitigate the risk of making poor purchasing choices. These reviews typically consist of textual feedback and ratings on a scale of 1 to 5. This study aims to evaluate the performance of product rating classification for Nutrimax Food Supplement using a hybrid Convolutional Neural Network – Long Short-Term Memory (CNN-LSTM) approach. The classification performance is assessed based on accuracy, precision, recall, and F1-score. CNN and LSTM are widely used techniques in text processing, each offering distinct advantages. CNN excels at extracting features from text, while LSTM is particularly effective in capturing and retaining sequential context over longer periods. By integrating these models, this study leverages their complementary strengths to enhance classification accuracy. The experimental results demonstrate that the hybrid CNN-LSTM approach achieves outstanding performance, with an accuracy of 0.994, precision of 0.994, recall of 1.00, and an F1-score of 0.996. These findings indicate that the hybrid CNN-LSTM model is highly effective for consumer review classification. The insights gained from this study can help businesses better understand customer feedback and improve product quality.

Keywords: Nutrimax Food Supplement, Klasifikasi, CNN, LSTM, Hybrid CNN-LSTM

1. Introduction

Suryaprana Nutrisindo, commonly known as Nutrimax Food Supplement, is a leading vitamin manufacturer in Indonesia. As a national distributor, the company specializes in the sale of vitamins and traditional medicines. Nutrimax Food Supplement offers approximately 70 varieties of vitamins and medicinal products, catering to a diverse demographic, including infants, children, the elderly, pregnant women, and individuals with specific health conditions. All Nutrimax products are halal-certified, ensuring they are suitable for Muslim consumers. These products are available at physical retail outlets such as Kimia Farma and local pharmacies, as well as through online marketplaces like Shopee and Tokopedia.

Nutrimax Food Supplement is recognized as a high-quality product and ranks among the top-selling items on the Shopee e-commerce platform, boasting an impressive rating of 4.9. Product ratings and consumer reviews play a crucial role in online purchasing decisions, as customers tend to rely on feedback from previous buyers to mitigate purchase risks [1]. Shopee's rating system includes both written reviews and a star-based evaluation ranging from 1 to 5, reflecting customer satisfaction. A 1-star rating indicates extreme dissatisfaction, whereas a 5-star rating signifies a highly satisfactory purchasing experience. Therefore, the 4.9 rating suggests that Nutrimax Food Supplement is perceived as delivering exceptional quality, outstanding service, and positive overall customer experience.

However, it is important to note that the 4.9 rating represents an average derived from consumer reviews, reflecting overall satisfaction. This aggregate score may not fully capture the variability in individual customer experiences. For instance, while the majority of consumers may provide high ratings, a small subset might offer lower evaluations, which could be overshadowed in the average score. Addressing this limitation, Nutrimax Food Supplement should conduct a detailed analysis and classification of individual consumer reviews. By systematically examining and categorizing feedback, the company can identify recurring patterns in negative reviews and pinpoint areas where its products or services can be improved.

Classification is a fundamental data mining technique used to predict the membership of data within specific groups based on its characteristics. It is one of the most extensively studied topics in data mining and machine learning, given its critical role in various practical applications, including prediction, pattern recognition, and decision-making [2].

Numerous studies in the field of healthcare have applied classification techniques. Traditional methods commonly used include Naïve Bayes, Support Vector Machine, and Decision Tree. For instance, research conducted by Nursyahfitri et al. [3] employed the Decision Tree method for classifying types of medications. However, with advancements in technology, the field of machine learning has seen significant progress. Deep learning, as a major branch of machine learning, has emerged as a solution for handling large and complex datasets. Leveraging artificial neural networks inspired by the human brain's structure, deep learning enables computers to process data in a more complex and profound manner, learning from intricate patterns [4, 5].

Convolutional Neural Networks (CNN) are a foundational model in the success of deep learning. Unlike other deep learning models, CNN distinguishes itself through an architecture specifically optimized for image data [6]. Although originally developed for image processing, CNN has also demonstrated effectiveness in addressing text data processing and speech recognition tasks. However, the application of CNN in text processing often overlooks the contextual relationships between parts of a document. This limitation has prompted researchers to explore alternative models such as Long Short-Term Memory (LSTM), which is designed with a sequential network architecture [7]. Text data serves as one example of sequential data.

Although LSTM excels in understanding contextual relationships within text, CNN remains superior in feature extraction from text documents. The combination of CNN and LSTM, therefore, is regarded as a more effective approach. This hybrid CNN-LSTM method facilitates the simultaneous use of spatial and sequential information. The CNN layers are responsible for extracting features from the input data, while the LSTM layers preserve long-term temporal information [8].

Several previous studies have successfully applied hybrid approaches, such as those conducted by Rehman et al [9]. They utilized a CNN-LSTM hybrid method to enhance the accuracy of sentiment analysis on movie reviews, with results demonstrating superior performance compared to traditional classification methods. Hermanto, Setyanto dan Luthfi [10] explored sentiment analysis on online media using a hybrid LSTM-CNN algorithm, where the CNN-LSTM hybrid outperformed both LSTM and LSTM-CNN methods.

Zhu, Chen dan Ye [11] conducted an analysis using a hybrid CNN-LSTM approach to human activity based on Micro-Doppler Radar. Furthermore, in the healthcare domain, Tasdelen and Sen [8] successfully applied the hybrid CNN-LSTM method to classify pre-miRNA, achieving strong performance and demonstrating the effectiveness of this approach for classifying pre-miRNA datasets in the health sector.

Building on the success of the previously presented hybrid CNN-LSTM model, this study aims to implement the integration of CNN and LSTM models in classifying the rating of Nutrimax Food Supplement products. The primary focus is on exploring how the integration of these models can enhance classification accuracy in analyzing and evaluating the ratings of this nutritional product.

2. Research Method

This study consists of several stages, including data preparation, the development of the hybrid CNN-LSTM model, and hypertuning processes to achieve optimal accuracy, as illustrated in Figure 1. The initial stage involves the collection, cleaning, and processing of data necessary for analysis. Following this, the hybrid CNN-LSTM model will be constructed by integrating both architectures. Finally, through hypertuning, the model parameters will be fine-tuned to achieve the best combination, ensuring optimal performance in classifying the Nutrimax Food Supplement product ratings.

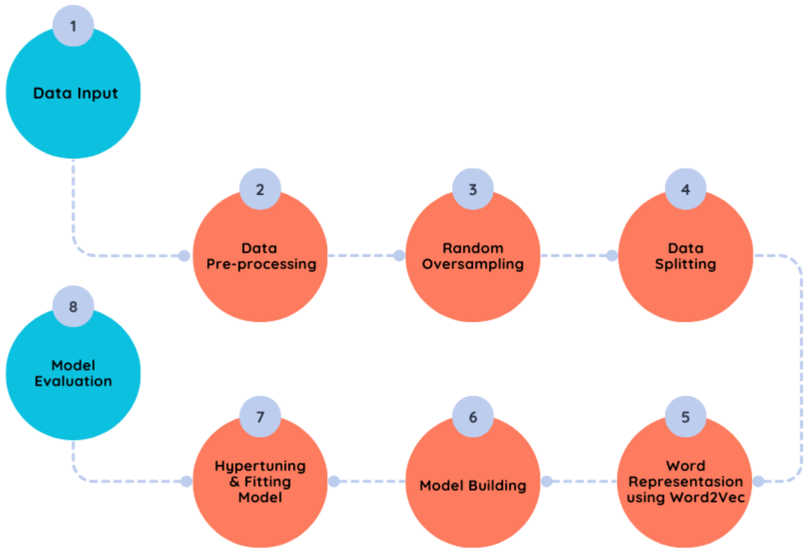

Fig 1: Research methods

2.1. Data Preparation

The data used in this study were extracted from product reviews and ratings of Nutrimax Food Supplement available on the Shopee e-commerce platform, accessible via https://shopee.co.id/nutrimaxonline. The dataset includes customer reviews and ratings ranging from 1 to 5 for the Nutrimax Food Supplement product. The data preparation process aims to identify and analyze consumer perceptions and evaluations of the product comprehensively.

Table 1. Evaluation Data of Nutrimax Food Supplement Products

No	Review	Rating
1.	**Indonesian version:** Khasiat: menjaga imun tubuh Rasa: cocok buat penderita asam lambung Harga: oke Vitamin c yg cocok banget buat penderita asam lambung. Pernah beli di drugstore, dan harga ini disaat promo. Ternyata klo normal, jauh banget ya di drugstore **English version:** Benefits: Supports immune health Taste: Suitable for individuals with acid reflux Price: Reasonable This vitamin C is ideal for people with acid reflux. Purchased at a drugstore during a promotion; however, the regular price at the drugstore is significantly higher.	5
2.	**Indonesian version:** Khasiat: Baru mau coba Rasa: Belum tau Harga: Lumayan Alhamdulilah barang udah sampe dan sesuai dengan pesanan termasuk lama banget terimakasih **English version:** Benefits: Yet to be tested Taste: Unknown Price: Reasonable Thankfully, the item has arrived and matches the order, despite the long delivery time. Thank you.	4
3.	**Indonesian version:** Khasiat: belum tau Rasa: gak ada rasa Harga: standar Maaf ya, kok beda warna sama saya beli di apotek.. yang beli di sini warna lebih pucat terus kok itu pada patah isi nya gompal2 gt... Jadi meragukan keaslian nya ini huhuhu **English version:** Benefits: Unknown Taste: Tasteless Price: Standard Apologies, but the color seems different from what I purchased at the pharmacy. The one bought here appears more pale, and the contents seem broken, with clumps inside. This raises doubts about its authenticity.	3
4.	**Indonesian version:** Pas mau beli lagi trnyata harganya naik, yang nutrimax c kids belum di refund **English version:** When attempting to purchase again, I found that the price had increased, and the refund for the Nutrimax C Kids has not yet been processed.	2
⋮	⋮	⋮
799.	**Indonesian version:** Aku kira softgell, soal nya lagi nyarik vitamin softgell. Jadi kurang memuaskan **English version:** I thought it was a softgel, as I was specifically looking for softgel vitamins. Therefore, it was somewhat unsatisfactory.	1

2.2. Data Pre-processing

Data preprocessing is a critical stage in data analysis. Chahid et al. [12] emphasize the significant role of data preprocessing in the success of machine learning and deep learning models, particularly in the medical and healthcare fields. At this stage, raw data is transformed into a format that can be understood and evaluated by computers and machine learning algorithms [13].

Preprocessing steps involve various important operations, such as converting all letters to lowercase, removing irrelevant content (e.g., stopword removal and non-alphabetic characters), and consolidating words with similar meanings to enhance prediction accuracy and reduce data variability. These techniques include stemming, lemmatization, and spell correction [14, 15].

2.3. Classification

Classification is a process aimed at categorizing data into predefined groups [16]. A classification model is built using training data and evaluated with testing data obtained through a train-test split technique.

Data splitting is a fundamental procedure in constructing a classification model, typically performed after the data preprocessing stage and prior to model architecture design [17]. The data split ratio can vary depending on the analysis requirements and objectives. However, Nguyen et al [18] recommend that the training set should be the largest. This ensures the model has access to a greater amount of information during training, thereby reducing the risk of overfitting, a condition where the model performs exceptionally well on training data but fails when faced with new data.

2.4. Random Oversampling
Random oversampling (ROS) is a technique employed to balance minority classes by increasing their sample size through random duplication. The aim is to equalize the number of samples in the minority class with that of the majority class. In practice, ROS entails the repeated addition of random samples from the minority class to the training dataset. This process continues until the sample count in the minority class matches that of the majority class [19].

2.5. Word2Vec
Text reviews cannot be processed directly by computers, requiring the transformation of textual data into a numerical format, such as vectors, for interpretation. Word2Vec is a word embedding technique used to represent words as vectors. This method has proven effective in analyzing semantic meaning and is beneficial for various tasks to optimize data and generate similar word vectors [20]. In this study, the word embedding used is Word2Vec.

Word2Vec is developed based on large corpora, such as Wikipedia. It consists of two popular models: Continuous Bag-of-Words (CBOW) and Skip-Gram. The key difference between Skip-Gram and CBOW lies in their neural network structure and the development process of each model. In the Skip-Gram model, when a word is input, the model identifies words that frequently appear alongside the input word. In contrast, the CBOW model uses the neural network to predict the target word based on the words surrounding it [21].

2.6. Activation Function
Activation functions play a key role in artificial neural networks, converting inputs into specific outputs [22]. These functions determine how input data is processed and passed through the network. In machine learning, various activation functions are used for specific purposes, such as ReLU (Rectified Linear Unit), Sigmoid, Softmax, and Tanh. The variety of activation functions allows models to address different types of data and tasks [23].

1. ReLU: effective in addressing the vanishing gradient problem, the mathematical formulation of the ReLU function is presented in Equation 1:

$$f(x) = max\,(0, x) \tag{1}$$

2. Sigmoid: produces an output between 0 and 1, as shown in Equation (2), and is commonly used in binary classification or two-class problems.

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{2}$$

3. Tanh: generates an output within the range of -1 to 1, as represented by Equation (3):

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3}$$

4. Softmax: Applied at the output layer for multi-class classification. Mathematically, the Softmax function is expressed in Equation (4):

$$p(x_i) = \frac{e^{x_i}}{\sum_{k=1}^{k} e^{x_j}} \tag{4}$$

2.7. Hybrid CNN-LSTM
CNN and LSTM are two widely used methods for addressing text classification challenges. CNN models excel in feature extraction, enabling the identification and retrieval of critical features from text documents. In contrast, LSTM models are capable of capturing contextual dependencies within the text and retaining information over extended periods. Figure 2 illustrates the workflow of the hybrid CNN-LSTM method applied in this study.

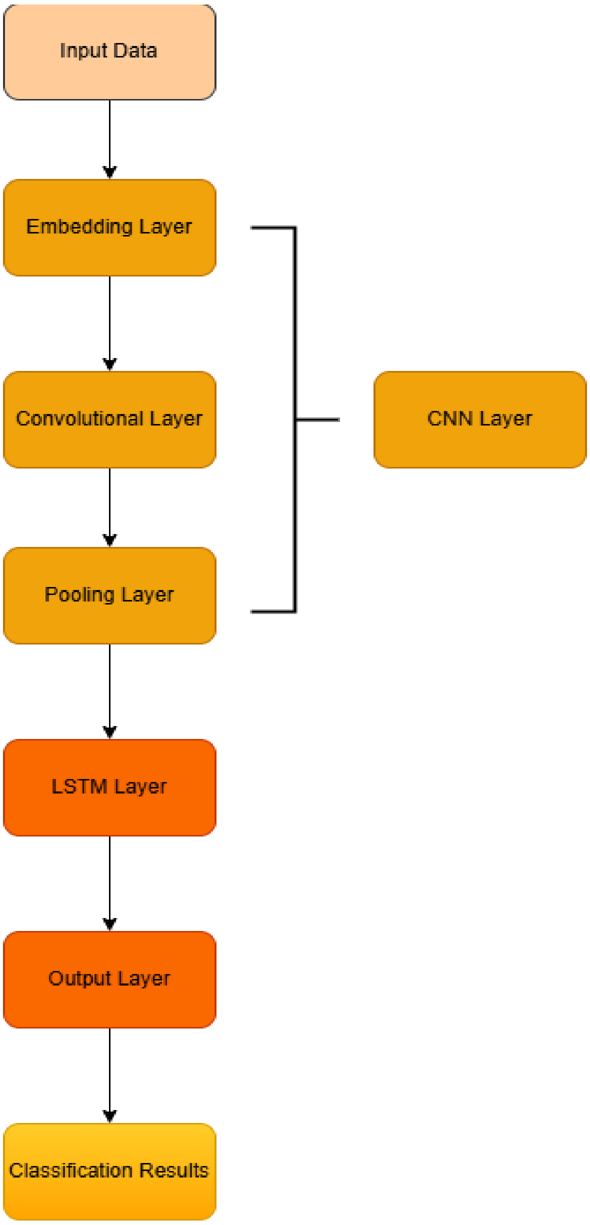

Fig 2: Workflow of the hybrid CNN-LSTM method

As the name suggests, the hybrid CNN-LSTM model is constructed by integrating the LSTM algorithm at the final layer of the CNN network. Prior to entering the LSTM layer, the input vector is processed through CNN. CNN processing involves two key steps: convolution and pooling. The convolution process is designed to extract essential features from the input data, while the pooling process reduces the data's dimensionality, thus lowering computational complexity. After these steps, the data is passed to the LSTM layer, where it handles sequence processing and captures temporal dependencies for the final classification. This hybrid approach leverages the strengths of CNN in spatial feature extraction and LSTM's ability to handle long sequence data, ultimately enhancing model performance in text classification tasks [24].

2.8. Model Evaluation

As stated by Nurvania, Jondri and Lhaksamana (25), a confusion matrix is a table or matrix used to evaluate the performance of a classification model. This matrix consists of four values that provide a detailed overview of the classification performance. These values include True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN).

The confusion matrix provides a clear overview of the model's performance in classification, displaying the number of correct and incorrect predictions for each category. Below is an illustration of the confusion matrix:

	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	True Positives (TPs)	False Positives (FPs)
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)

Fig 3: Confusion matrix

The matrix plays a crucial role in model performance analysis as it allows for the evaluation of the model not only in terms of accuracy but also through other evaluation metrics such as the F1-score. The F1-score is a metric that considers data distribution, measured based on precision and recall, and is particularly valuable in research involving imbalanced classification. Utilizing the F1-score provides deeper insights into how the model handles imbalanced data distributions, making the performance evaluation more comprehensive and accurate.

3. Results and Discussion

3.1. Data Pre-processing

Data preprocessing aims to clean and prepare the data for easier analysis in subsequent stages. This process is crucial because raw data often lacks a structured format and contains noise that can interfere with analysis. In this study, preprocessing consists of five main stages: lowercasing, data cleaning, stopword removal, tokenization, and stemming. Below is a detailed explanation of each stage:

a. Lowercasing: converting all text into lowercase letters.
b. Data cleansing: eliminating irrelevant characters or symbols that do not contribute to the analysis.
c. Stopword removal: removal of common words that do not convey significant information, such as 'and', 'or', and 'but'.
d. Tokenization: the process of breaking text into smaller units, such as words or phrases.
e. Stemming: reducing word variations by transforming words into their base forms.

Table 2 illustrates the data before and after preprocessing:

Table 2: Data Pre-processing

Before	After
Khasiat: menjaga imun tubuh\nRasa: cocok buat penderita asam lambung\n Harga: oke\nVitamin c yg cocok banget buat penderita asam lambung. \nPernah beli di drugstore, dan harga ini disaat promo. Ternyata klo normal, jauh banget ya di drugstore	[khasiat, jaga, imun, tubuh, rasa, cocok, buat, derita, asam, lambung, harga, oke, vitamin, c, cocok, banget, buat, derita, asam, lambung, pernah, beli, drugstore, harga, saat, promo, ternyata, normal, jauh, banget, drugstore]

3.2. Data Visualization

The next step involves data visualization, aimed at examining the distribution and comparison of ratings from 1 to 5 stars. Visualization helps determine whether the rating distribution is balanced. Understanding the rating distribution pattern allows for the implementation of appropriate measures to address potential biases or imbalances in the dataset, thereby enhancing the accuracy and significance of the analysis. This visualization is presented in Figure 4.

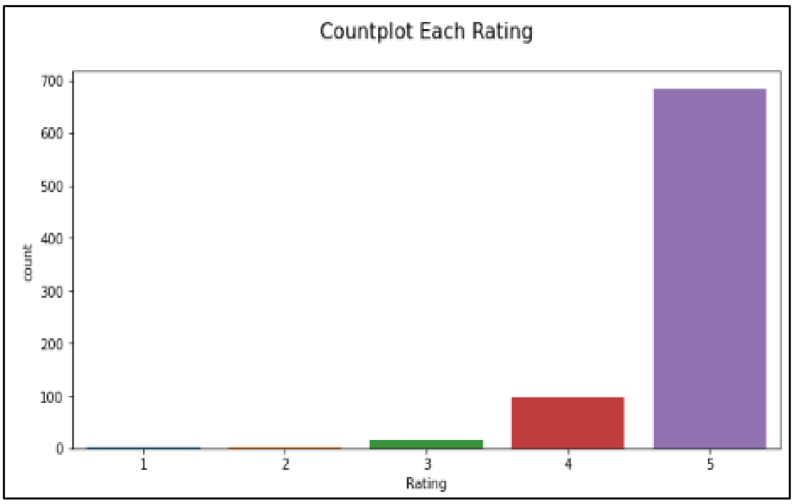

Fig 4: Data visualization

3.3. Random Oversampling

Based on the analysis in Figure 4, a significant imbalance in the distribution of data across ratings 1 to 5 is observed. This condition highlights the need for an effective approach to balance the data. The method employed in this study is the ROS technique, where additional samples are randomly replicated into the minority classes, specifically ratings 1 through 4. This step aims to ensure that the number of data points in each class is balanced with the majority class, rating 5.

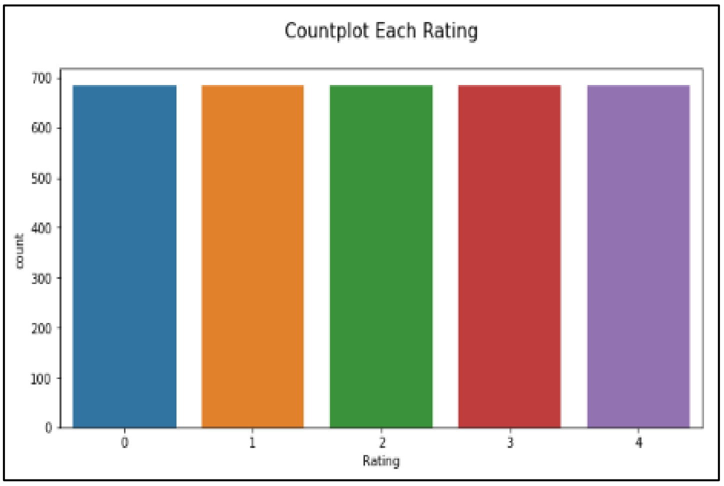

Fig 5: Results of the ROS analysis

Figure 5 illustrates the results of the data balancing or resampling process using the ROS method. The figure shows that the data, after undergoing the ROS process, have a similar quantity to the majority class, totaling 684 data points. As a result, the overall data set after the ROS process contains 3,420 data.

3.4. Data Splitting

The Nutrimax Food Supplement product rating data is divided into two sets: training data and testing data. The training data is used to train the model and determine the optimal parameters, while the testing data is used to evaluate the performance of the trained model.

The data is split with an 80% training and 20% testing ratio, as well as a 90% training and 10% testing ratio. Details of this data partition are presented in Table 3.

Table 3: Data Splitting

Training		Testing	
80%	90%	20%	10%
2736	3078	684	342

3.5. Building the Hybrid CNN-LSTM Model

The Hybrid CNN-LSTM integrates the CNN and LSTM layer structures into a single model. In this architecture, the CNN layer is placed at the beginning, prior to passing the data to the LSTM layer. The CNN model consists of an embedding layer, convolutional layers with ReLU activation, max pooling layers, dropout layers, and batch normalization. Following this, the data is passed to the LSTM layer, which includes LSTM units, a hidden LSTM layer with three activation functions—one hyperbolic tangent function and two sigmoid functions—dropout layers, batch normalization, and an output layer with a softmax activation function at the final layer. This configuration enables the model to optimize the individual capabilities of each layer in processing both sequential and spatial information, facilitating more complex and adaptive modeling of data.

The first layer in this model is the word embedding layer, which includes the parameters input_dim, output_dim, and input_length. The input_dim parameter refers to the size of the vocabulary, which consists of 1,960 words. The output_dim parameter indicates the dimension of the resulting embedding, set at 50. The input_length parameter represents the length of the input word vectors, fixed at 30. As a result, the word embedding layer transforms words in the vocabulary into 50-dimensional vectors, where each word is represented by a vector of the same length, specifically 30. Through this embedding layer, the vocabulary is represented as vectors with more meaningful representations in a reduced-dimensional space.

The subsequent layer is a one-dimensional convolutional layer comprising 32 filters with a kernel size of 3, utilizing the ReLU activation function. This convolutional layer extracts features using filters in the form of kernels, producing output as feature maps. These feature maps represent key features in a lower-dimensional space. The convolutional process is performed twice, as the model incorporates two consecutive convolutional layers to enhance classification performance. Following the convolutional layers, the output is processed through dropout and batch normalization layers to prevent overfitting and accelerate training convergence.

After passing through the convolutional layers, the data is forwarded to the pooling layer. In this study, one-dimensional max pooling with a pool size of 2 is utilized. This max pooling operation extracts the maximum value from the feature map at each grid, helping to reduce and prevent overfitting in the model.

Subsequently, the data from the CNN layer is transferred to the LSTM layer. The first layer of the LSTM section is an LSTM layer with 100 units. The output from this LSTM layer then passes through a dropout layer with a rate of 0.2, deactivating 20% of the total neurons, and a batch normalization layer to further prevent overfitting.

The following layer is a hidden or dense layer with 32 nodes, employing one Tanh activation function and two Sigmoid activation functions. The final layer in the LSTM structure is the output layer with 5 nodes, utilizing a Softmax activation function, as the model is designed for multiclass classification with an output range of values from 1 to 5.

3.6. Hypertuning and Fitting Model

Hypertuning aims to identify the optimal parameter combination for the developed model. A commonly used

method to determine the best parameters is trial and error. However, due to the large number of parameters that need to be tested, this method is inefficient and time-consuming. For this reason, GridSearchCV was employed in this study as a hypertuning method. It works by selecting hyperparameter combinations and testing each combination individually.
The parameters optimized through the hypertuning process include dropout, the number of epochs, and batch size. Additionally, early stopping with a patience value of 20 was implemented to halt model training if performance did not improve after 20 epochs. Table 4 provides a detailed breakdown of the optimized parameter combinations.

Table 4: Optimized Parameter

Parameter	Value
Dropout	0.2, 0.3, dan 0.4
Epoch	50, 100, dan 200
Batch size	32, 64, dan 128

Based on the hypertuning process conducted, the optimal parameter combination for the first data splitting scheme (80% training data) includes a batch size of 64, a dropout rate of 0.2, and 200 epochs. In contrast, for the second data splitting scheme (90% training data), the best combination found consists of a batch size of 32, a dropout rate of 0.3, and 200 epochs.
The results of training the hybrid CNN-LSTM model with two different data partitioning schemes are illustrated through accuracy graphs in Figures 6 and 7. Figure 6 displays the accuracy graph for the first data partitioning scheme, where 80% of the data is used for training and 20% for testing. In contrast, Figure 7 shows the accuracy graph for the second data partitioning scheme, with 90% of the data allocated for training and 10% for testing. These graphs visualize the changes in accuracy values throughout the training process for both data partitioning schemes.

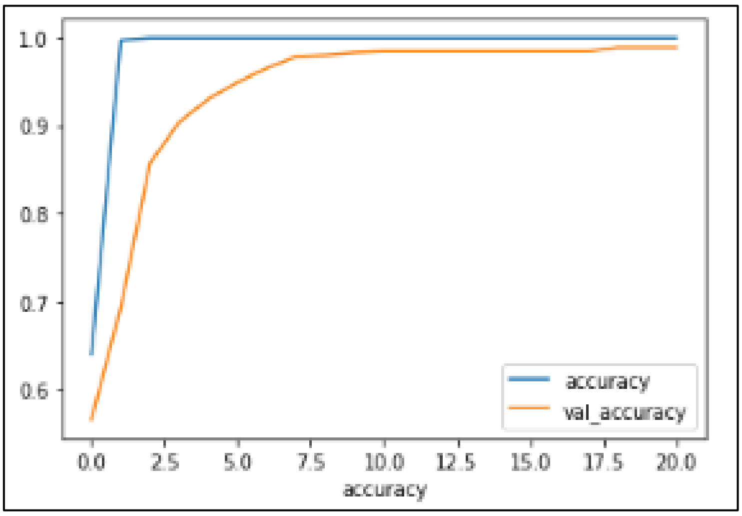

Fig 6: Accuracy graph of the first scheme

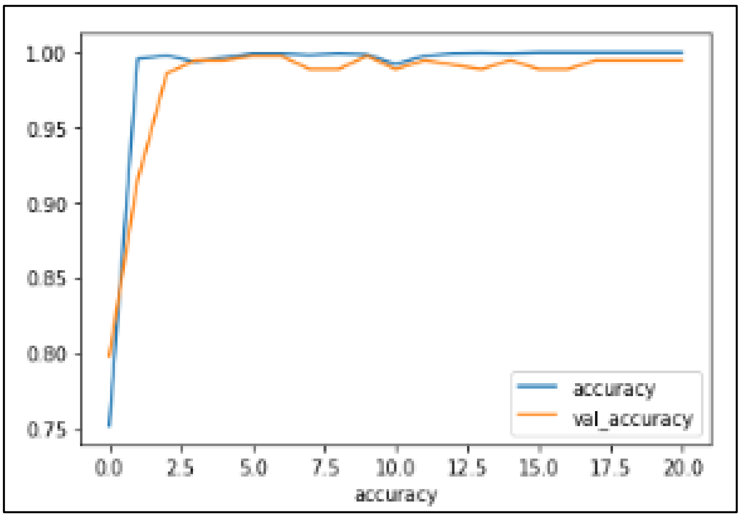

Fig 7: Accuracy graph of the second scheme

Based on Figures 6 and 7, it is evident that each scheme achieves a similar accuracy rate, exceeding 99%. However, determining the best model solely based on the accuracy graphs is challenging. To facilitate a more thorough analysis and comparison of model effectiveness, the next step involves evaluation using a confusion matrix. This matrix provides more detailed information about the model's ability to classify each class, allowing the identification of classes that are either particularly difficult or easy for the model to predict. Consequently, this evaluation will aid in selecting a more optimal data partitioning scheme for the hybrid CNN-LSTM model.

3.7. Model Evaluasi

The model evaluation results using the confusion matrix for both data splitting schemes are visualized in Figures 8 and 9.

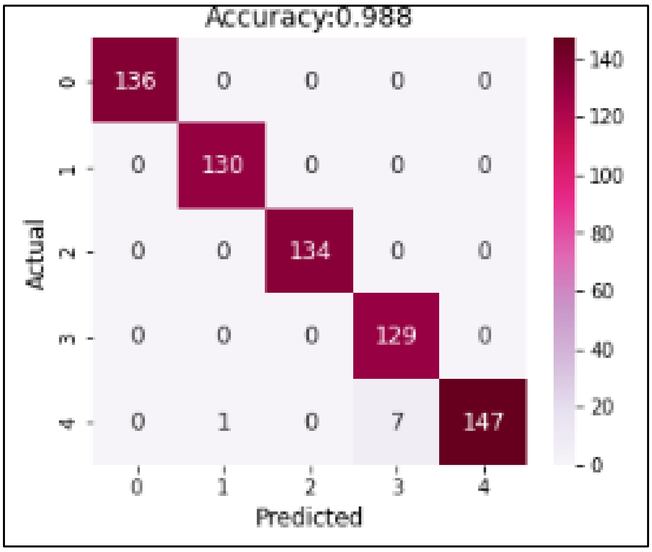

Fig 8: Confusion matrix for the first scheme

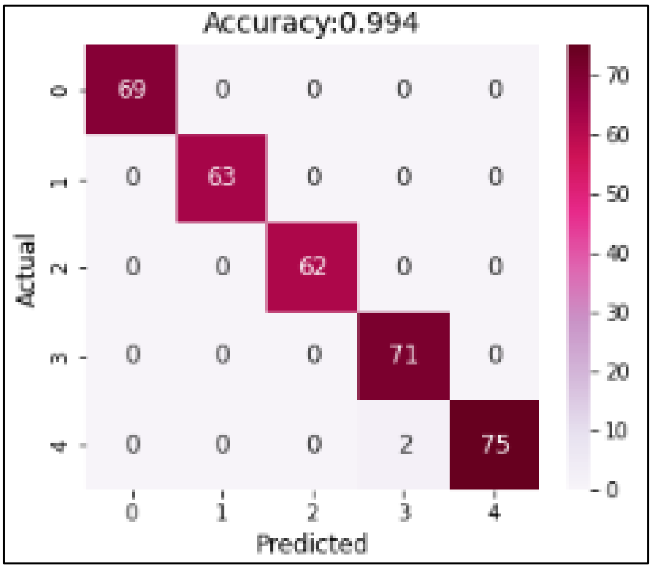

Fig 9: Confusion matrix for the second scheme

Classes correctly classified by the model are positioned along the diagonal line, while classification errors appear outside this line. Based on this, it can be concluded that the model successfully classifies most ratings accurately. In the first scheme, eight instances were misclassified: one as rating 2 and seven as rating 4, when the actual class was rating 5. In the second scheme, fewer instances were misclassified, with only two errors, both of which were incorrectly classified as rating 4, while the true class was rating 5.

Furthermore, to facilitate the understanding and analysis of the model's performance, evaluation metrics were tabulated based on the values of TP, TN, FP, and FN from the confusion matrix. The results of this tabulation are summarized in Tables 5 and 6.

Table 5: Evaluation Metrics for the First Scheme

Rating	Precision	Recall	F1-Score
1	1.00	1.00	1.00
2	0.99	1.00	1.00
3	1.00	1.00	1.00
4	0.95	1.00	0.97
5	1.00	0.95	0.97
Macro Average	0.988		

Table 6: Evaluation Metrics for the Second Scheme

Rating	Precision	Recall	F1-Score
1	1.00	1.00	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
4	0.97	1.00	0.99
5	1.00	0.97	0.99
Macro Average	0.994		

The analysis of the evaluation metrics in Tables 5 and 6 reveals that the model employing the second data partitioning scheme outperforms the model with the first partitioning scheme. This finding aligns with prior research emphasizing the importance of a larger training data ratio compared to the testing data. Consequently, it can be concluded that increasing the training data size improves classification performance, even in the case of imbalanced datasets.

4. Conclusion

Based on the results and discussion presented in the previous sections, it can be concluded that the classification of Nutrimax Food Supplement product ratings using the hybrid CNN-LSTM method demonstrates superior performance, particularly with the second data split scheme of 90% training data and 10% testing data. The model achieved an average macro score of 99.4%.

This high macro average indicates that the model did not experience overfitting, as all evaluation metrics yielded strong results. Furthermore, the F1-score analysis shows that the proposed model effectively addresses the data imbalance issue encountered during classification. Therefore, this model represents a promising approach or solution for identifying common patterns and uncovering potential improvements in Nutrimax Food Supplement products or services.

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