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Look Alike-Sound Alike Prediction as A Tool for Patient Safety

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Abstrak

Laporan dari WHO menyatakan salah satu penyebab medication error tertinggi berupa obat-obatan Look Alike – Sound Alike dikarenakan bentuk dan nama obat antara yang satu dengan lainnya terdapat kemiripan baik dari pengucapan maupun penulisan, sehingga terjadi kesalahan dalam menerima informasi tentang obat, tentu hal ini akan berpengaruh terhadap keselamatan pasien. Usaha untuk mengurangi medication error sudah banyak dilakukan seperti diadakan pelatihan obat, pengelolaan obat serta penyimpanan dan pelabelan obat. Namun itu semua mengarah pada human error sehingga diperlukan suatu pemanfaatan teknologi kecerdasan buatan yang dapat secara otomatis mendeteksi dan belajar mandiri sehingga penyebab medication error berupa Look Alike – Sound Alike dapat berkurang. Deep learning merupakan bagian dari kecerdasan buatan yang cara kerjanya memberikan solusi dengan akurat dan otomatis. Algoritma Recurrent Neural Networks merupakan salah satu metode deep learning yang sudah dibuktikan keakurasiannya dalam memprediksi berdasarkan penelitian-penelitan yang telah dilakukan sebelumnya. Pada penelitian ini melakukan prediksi Look Alike – Sound Alike menggunakan Recurrent Neural Networks dengan tujuan sebagai alat bantu untuk mengurangi medication error sehingga keselamatan pasien menjadi terjaga. Akurasi yang dihasilkan yaitu 99% untuk pelatihan dan 81% untuk pengujian.

Kata kunci— *Prediksi; Medication Error; Look Alike – Sound Alike; Deep learning; Recurrent Neural Networks*

Abstract

A report from WHO stated that one of the highest causes of medication errors in the form of Look Alike - Sound Alike drugs is due to the shape and name of the drug between one and another having similarities both in pronunciation and writing, so that errors occur in receiving information about the drug, of course this will affect patient safety. Efforts to reduce medication errors have been carried out, such as drug training, drug management and drug storage and labeling. However, all of this leads to human error, so it is necessary to utilize artificial intelligence technology that can automatically detect and learn independently so that the cause of medication errors in the form of Look Alike - Sound Alike can be reduced. Deep learning is part of artificial intelligence that works by providing solutions accurately and automatically. The Recurrent Neural Networks algorithm is one of the deep learning methods that has been proven to be accurate in predicting based on previous studies. In this study, Look Alike - Sound Alike predictions were made using Recurrent Neural Networks with the aim of being a tool to reduce medication errors so that patient safety is maintained. The resulting accuracy is 99% for training and 81% for testing.

Keywords— *Prediction; Medication Error; Look Alike – Sound Alike; Deep learning; Recurrent Neural Networks*

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1. INTRODUCTION

Patient safety is a major concern in health care. One of the problems that often occurs in drug administration is medication error in the form of speech, form, and name of drugs that are almost the same called Look Alike Sound Alike (LASA) (Integrated health services team, 2023). Medication errors not only occur in Indonesia but in developed countries such as the UK, medication errors reached 10.7% of the incidence rate between January-March 2018 (Bryan R, et al, 2021). One of the solutions to the problem of medication error is related to the storage of LASA drugs in pharmacies (Dasopang ES, et al, 2022), but only 50% are in accordance with the laws and regulations for storing LASA drugs (Ministry of Health RI, 2022). The problem of medication errors has been tested using Chi-Square that there is no relationship between knowledge and management of LASA drugs and management and errors in taking LASA drugs by pharmacists (Mukhlis M, et al, 2019), causing the occurrence of medication errors to remain high.

Research on LASA has been conducted by (Samudra AG, et al, 2022), this study was conducted by giving a questionnaire sheet to determine the level of knowledge about LASA drugs to Pharmaceutical Technical Personnel who work at the Bengkulu City Pharmacy. The results of the Chi-Square test stated that there was no significant relationship between knowledge and management of LASA medication errors. Another study (Amrullah H, 2022) used a quasi-experimental design method with a pre and post analysis approach and used a control group as a comparison, which aims to determine the effect of training on the suitability of LASA drug storage. The results of this study are that it is better to establish a list of LASA drugs as a reference for health service providers in carrying out storage. Research conducted by (Rika N, et al, 2021) uses a quantitative approach method with a correlational research type, which aims to determine the effect of storage and marking of high alert drugs and LASA. The results of this study are the storage and marking of high alert drugs and LASA affect the risk of human error. Research related to LASA was conducted qualitatively by (Zafirah AD, et al, 2022) and (Angraini D, et al, 2021) which found that the cause of adverse events was an error in administering the drug was negligence of the staff, hospital policies in storing and marking high alert drugs and LASA had not used the Tallman Lettering method, poor communication and showed medication errors occurred in the prescribing error, dispensing error, and administration error phases.

Software is needed to find drug similarities, because LASA can confuse pharmacists, nurses, and patients (Emmerton L, et al, 2020). Recently, the application of artificial intelligence using deep learning algorithms can overcome medication errors in the form of LASA (Roy A, 2022), because it can increase safety and can be utilized as health care (Ellahham S, et al, 2019). Artificial intelligence and automation methods such as deep learning are one of the most accurate tools to avoid errors due to medication errors (Diez IL, et al, 2020). One of the deep learning algorithms that produces high accuracy is Recurrent Neural Networks (RNN) for stock predictions (Suyudi MAD, et al, 2019) Covid predictions (Ghozi AA, et al, 2022), and for cement sales forecasting (Achmalia AF, et al, 2020). Recurrent Neural Networks also showed accuracy rates of 86%, 88%, and 96% compared to other deep learning algorithms namely Naïve Bayes and Support Vector Machine for sentiment analysis of e-commerce product reviews (Zuraiyah TA, et al, 2023)[7].

The utilization of artificial intelligence with the Recurrent Neural Networks algorithm is expected to be a tool to overcome medication errors related to LASA given the high accuracy of the RNN algorithm. Based on this background, the problem formulation in this study is how to create a tool to reduce medication errors that occur due to LASA to improve patient safety using the Recurrent Neural Networks algorithm.

2. METHODS

2.1 Recurrent Neural Network (RNN)

Recurrent Neural Networks (RNN) algorithms represent a type of architecture in artificial neural networks (ANNs) specifically designed for sequential data processing (Pipin SJ, et al, 2023). RNN architectures are commonly used to handle inputs associated with sequential data. RNNs have the ability to retain, archive, and analyze previous complex signals over long periods of time. Unlike the JST learning mechanism, the RNN learning process does not eliminate historical data. This key feature serves as the main difference between RNNs and JSTs (Yuniar A, et al, 2023). By incorporating a mechanism that repeats past information in its structure, this approach enables the storage of past data in memory, facilitating data pattern recognition and subsequent utilization for predictive purposes (Kusuma NPN, 2023).

2.2 Long Short Term Memory (LSTM)

The evolution of the RNN architecture introduced by Horchreiter & Schmidhuber is the Long Short Term Memory (LSTM) method (Selle N, et al, 2022). RNN consists of an input layer, hidden layer and output layer. The weakness of RNN is that there is still a problem regarding vanishing gradient as the length of sequential data to be trained increases. The difference lies in how the conputation process in the hidden layer or what is called the contents of the memory cell as illustrated in Figure 1.

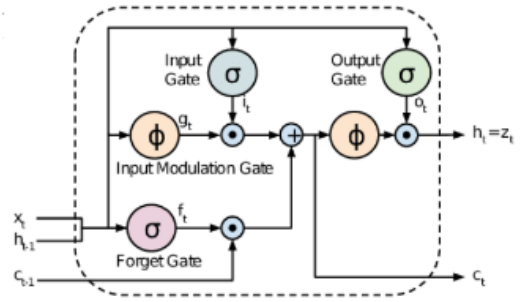

Figure 1 LSTM Model

The way LSTM works is based on gates that perform certain functions (Shiri FM, et al, 2023), which consists of three gates, namely first, input gate to update the internal state based on the current input and the previous internal state. Second, forget gate to determine how much of the previous internal state will be removed. The last gate, output gate to set the output of the system. LSTM has a calculation for weight updates with the following formula:

$$
\begin{aligned}
h^{(t)} &= g_0^{(t)} f_h\left(s^{(t)}\right) \\
s^{(t-1)} &= g_f^{(t)} s^{(t-1)} + g_i^{(t)} f_s\left(wh^{(t-1)}\right) + uX^t + b \\
g_i^{(t)} &= sigmoid\left(w_i h^{(t-1)}\right) + u_i X^{(t)} + b_i \\
g_f^{(t)} &= sigmoid\left(w_f h^{(t-1)}\right) + u_f X^{(t)} + b_f \\
g_o^{(t)} &= sigmoid\left(w_o h^{(t-1)}\right) + u_o X^{(t)} + b_o
\end{aligned}
\qquad (1)
$$

Description:

f_h, f_s = the activation functions of the system state and internal state,

g = The gating operation, denoted as is a feedforward neural network with a sigmoid activation function

i, f, o = the input gate, output gate, and forget gate

2.3 Metric Evaluation

Metric evaluation is used to measure the accuracy of the prediction of the suitability between existing data and predicted data. This stage is the stage of evaluating the performance

of the LSTM algorithm using the Confusion Matrix, namely: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN), as in the following table:

Tabel 1. Confusion Matrix

Actual Class	**Prediction**	
	Positives	Negatives
Positives	TP	FN
Negatives	FP	TN

True Positives (TP) is the number of positive data that is correctly detected, while False Negatives (FN) is the number of positive data that is detected as negative data. True Negatives (TN) is the number of negative data that is correctly detected, while False Positives is negative data that is detected as positive data (Rozi IF, et al, 2020).

Precision, Recall, and F-Measure values are obtained from the results of TP, TN, FP, and FN. Precision is the positive data that is predicted correctly divided by the number of positive classes predicted. Recall is the number of positive predictions divided by the number of positive classes in the testing data. F-Measure is a measure of the accuracy of testing that is used to produce a weighted harmonic mean of precision and recall. These equations can be shown as follows:

$$Precision = \frac{TruePositives}{TruePositives+FalsePositives}$$

$$Recall = \frac{TruePositives}{TruePositives+FalseNegatives} \quad (2)$$

$$F-Measure = 2 * \frac{1}{\frac{1}{Precision}+\frac{1}{Recall}}$$

2.4 System Design

One of the main problems of medication errors is related to LASA drugs, to help distinguish LASA drugs from those that are not, utilizing artificial intelligence in the field of deep learning using the Recurrent Neural Networks algorithm, Long Short Term Memory architecture. The problem approach process can be seen in Figure 2.

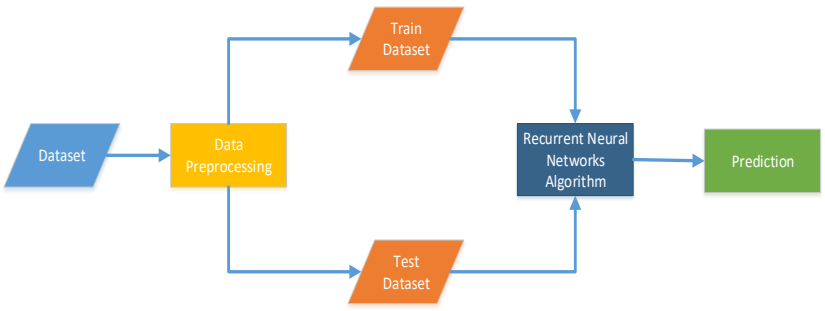

Figure 2 Troubleshooting Flow

The proposed troubleshooting flow is divided into:

2. 4.1 Data Pre-processing

In this process, data preparation is carried out first, namely collecting drug data. The dataset is obtained from the pharmacy department at Citra Paramedika Hospital in Yogyakarta. Then data preprocessing is carried out, namely cleaning the data until the data is ready to be used, the data is divided into training data and test data. Here are some LASA drug data shown in Table 2.

Table 2. List Medicine LASA

Medicine	Category
Alloris	NOT LASA
Alpara	NOT LASA
Alprazolam 0,5mg	NOT LASA
Ambevent	LASA
Ambroxol 15/5mg syr	NOT LASA
…	…
Aminofluid	NOT LASA
Aminophyllin	LASA
Aminopilin inj	NOT LASA
Amiodarone 200mg	LASA
Amiodarone HCL inj	LASA

2. 4.2 RNN Implementation

Problem solving using the RNN algorithm and LSTM architecture is using the prediction method. In this method, the Recurrent Neural Networks algorithm is used to select the best model using training data, then test data can be inputted to be processed using the RNN algorithm and LSTM architecture to get LASA predictions. The training and testing process can be described in the prediction system flowchart which can be seen in Figure 3.

The training process using the RNN algorithm and LSTM architecture aims to produce the best model from the training dataset. The training dataset is obtained from the results of data preprocessing, namely cleaning the data first and then dividing the data into two, namely the training and test datasets. After getting the best model, the next step is to carry out the testing process using the test dataset, then testing is carried out using the Recurrent Neural Networks algorithm which will pro4uce LASA prediction results.

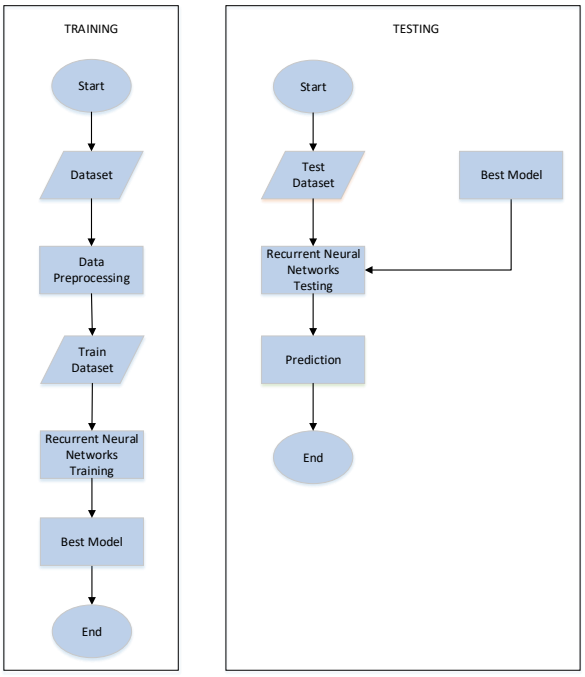

Figure 3 LASA Drug Prediction Flowchart

Recurrent Neural Networks differ from feed-forward neural networks by generating outputs based on the sequential arrangement of input layers and hidden layers. As a result, this procedure can be described more easily. RNNs operate by handling inputs and processing them alongside various previously acquired information. The determination of the outcome or decision generated from a particular input is influenced by the pre-existing information system.

This is due to the fact that Recurrent Neural Networks have an internal memory that is capable of maintaining a collection of information. The behavior of an RNN does not show immediate proportionality as observed in feed-forward neural networks; instead, it traverses loops that include some historical information. Therefore, the RNN not only evaluates the current input but also takes into account all previous information (Jabat D, et al, 2024). The following differences between feed-forward neural networks and RNNs are illustrated in Figure 4.

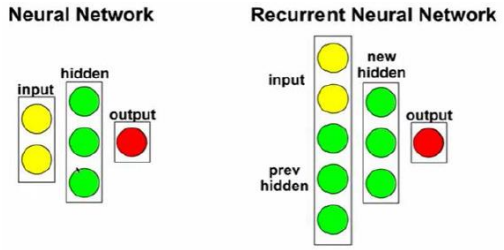

Figure 4 The difference between feed-forward neural networks and RNNs

3. RESULTS AND DISCUSSION

LASA prediction uses two processes, namely the training and testing processes.

3.1 Training Process

In the training process, data preprocessing is carried out which consists of changing uppercase letters to lowercase letters, removing spaces before and after words, and replacing spaces that separate two or more words with underscores. The following can be seen in Figure 5 for the preprocessing flowchart.

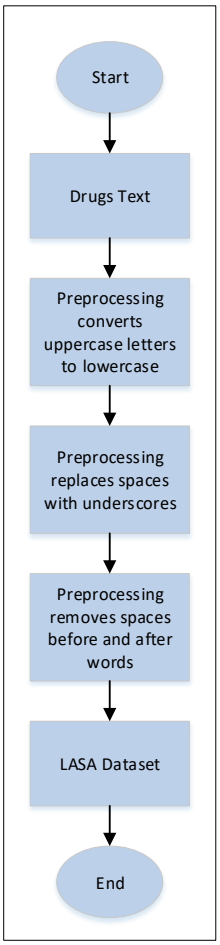

Figure 5. Preprocessing Flowchart

The dataset that has been obtained is divided into two classes by labeling, namely LASA and not LASA. Furthermore, the training process is carried out repeatedly to produce an RNN model with a high enough training accuracy to predict accurately.

3.2 Testing Process

There are two tests carried out, consisting of testing the optimization model and testing the amount of data. While the dataset used consists of 836 drug data which includes LASA and non-LASA data.

3.2.1 Optimization Model Testing

This test compares two optimization methods, namely: Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (Adam). These two methods have their own advantages and disadvantages, so testing is done with a different number of epochs, due to different convergent rates. The results can be seen in Table 3, Figure 6 and Figure 7 as follows:

Table 3. SGD optimization model comparison

Learning Rate	Train Accuration	Train Loss	Test Accuration	Test Loss
0,001	0,23	0,69	0,17	0,7
0,005	0,54	0,67	0,38	0,69
0,01	0,56	0,67	0,18	0,71
0,05	**0,67**	**0,64**	**0,76**	**0,55**
0,1	0,21	0,73	0,82	0,65
0,5	0,45	0,74	0,17	0,88

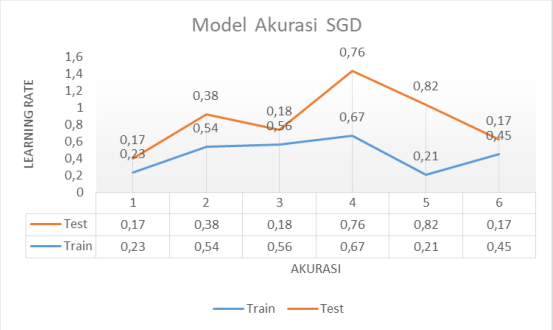

Figure 6 SGD Accuration Model

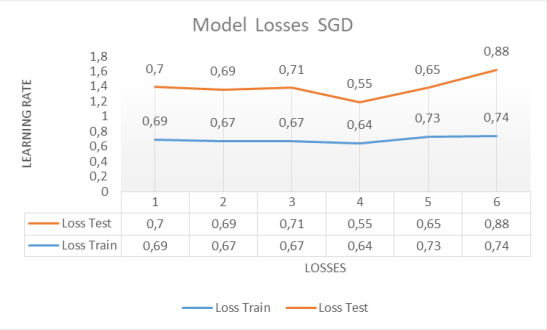

Figure 7 SGD Losses Model

Based on Table 1, Figure 6 and Figure 7, the highest accuracy is obtained when the Learning Rate is 0.05, which results in 67% train accuracy and 76% test accuracy with 65% train loss and 55% test loss. Different results are shown in the Adam optimization model as shown in Table 4, Figure 8, and Figure 9 below.

Table 4. Adam optimization model comparison

Learning Rate	Train Accuration	Train Loss	Test Accuration	Test Loss
0,0001	0,6	0,61	0,38	0,69
0,0005	0,95	0,16	0,82	0,53
0,001	0,97	0,04	0,81	0,44
0,005	**0,99**	**0,01**	**0,81**	**0,62**
0,01	0,98	0,05	0,81	0,58
0,05	0,83	0,4	0,55	0,88

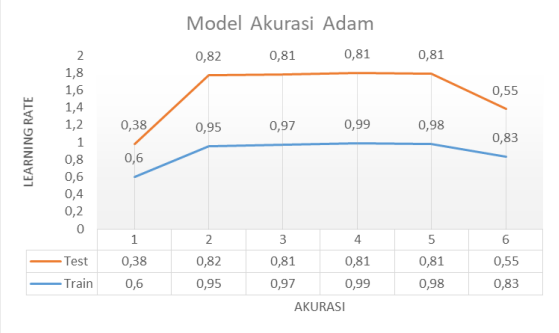

Figure 8 Adam Accuration Model

Figure 9 Adam Losses Model

Testing the optimization model using Adam's method obtained higher accuracy compared to the SGD method, namely: 99% train accuracy and 81% test accuracy with 1% loss train and 62% loss test. However, the learning rate used is different, namely 0.005.

3.2.2 Data Testing

Data testing uses the best model, namely the Adam model. This test consists of sharing a different number of datasets, with the aim of knowing the best accuracy. The test results can be seen in Table 5 below.

Table 5 Testing Data

Data Train	Data Test	Akurasi Train	Loss Train	Akurasi Test	Loss Test
50	50	0,81	0,45	0,68	0,63
60	40	0,69	0,54	0,78	0,52
70	**30**	**0,99**	**0,01**	**0,81**	**0,62**
80	20	0,94	0,19	0,81	0,46

Based on Table 4, it shows that the highest accuracy is obtained in the division of datasets 70 for train data and 30 for test data which results in 99% train accuracy and 81% test accuracy.

4. CONCLUSIONS

This research produces LASA predictions by comparing two tests. Firstly testing the SGD optimisation model with Adam, both have advantages and disadvantages. SGD requires more epochs due to its slow convergence rate but is stable and robust to overfitting. While Adam has a faster convergence rate that can cause overfitting, but is robust to noise and only requires a small number of epochs. The results of testing the two models produce different accuracies, the accuracy of the Adam model is 81% compared to the accuracy of the SGD model 76%. So that the Adam model is used to perform the LASA prediction process. The second test was conducted to compare the number of datasets, the highest accuracy resulted from the division of 70 datasets for train data and 30 for test data, namely 99% train accuracy and 81% test accuracy.

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REFERENCES

[1] Tim Integrated Health Services (HIS). Medication Safety for Look-Alike, Sound-Alike Medicines. World Health Organization. 2023.

[2] Bryan R, Aronson JK, Williams A, Jordan S. The problem of look-alike, sound-alike name errors: Drivers and solutions. Vol. 87, British Journal of Clinical Pharmacology. 2021.

[3] Dasopang E.S, Utami A, Hasana F, Siahaan D.N, Harefa N.S. Profil Penyimpanan Obat LASA (Look Alike Sound Alike) Pada Beberapa Apotek di Kota Medan. Vol 14, No 2. Jurnal Farmasi Indonesia. 2022.

[4] Departemen Kesehatan Republik Indonesia mengenai Permenkes No 58 Tahun 2014. Peraturan Menteri Kesehatan Republik Indonesia tentang Standar Pelayanan Kefarmasian di Rumah Sakit.

[5] Muhlis M, Andyani R, Wulandari T, Sahir AA. Pengetahuan Apoteker tentang Obat-obat Look-alike Sound-alike dan Pengelolaannya di Apotek Kota yogyakarta. Jurnal Farmasi Klinik Indonesia, Vol 8 No 2. 2019.

[6] Emmerton L, Curtain C, Swaminathan G, Dowling H. Development and Exploratory Analysis of Software to Detect Look-Alike Sound-Alike Medicine Names. International Journal of Medical Informatics. 2020.

[7] Roy A. Identification in Drug Presciption using Artificial Intelligence. SSRN. 2022.

[8] Ellahham S, MD, Ellahham N. Application of Artificial Intelligence in the Health Care Safety Context: Oppurtunities and Challenges, American Journal Medical Quality 1-8. 2019.

[9] Diez IL, Escriba CF, Lopez MAP, Lastra CF, Marino L, Modamio P. Prevention Strategies to Identify LASA Errors: Building and Sustaining a Culture of Patient Safety. BMC Health Services Research. 2020.

[10] Suyudi MAD, Esmeralda CD, Maspupah A. Prediksi Harga Saham menggunakan Metode Recurrent Neural Network. Seminar Nasional Aplikasi Teknologi Informasi (SNATi). 2019.

[11] Ghozi AA, Aprianti A, Dimas ADP, Fauzi R. Analisis Prediksi Data Kasus Covid-19 di Provinsi Lampung Menggunakan Recurrent Neural Network (RNN). Indonesian Journal of Applied Mathematics, Vol 2 (1). 2022.

[12] Achmalia AF, Walid, Sugiman. Peramalan Penjualan Semen Menggunakan Backpropagation Neural Network dan Recurrent Neural Network. UNNES Journal of Mathematics, Vol 9 (1). 2020.

[13] Zuraiyah TA, Mulyati, Harahap GHF. Perbandingan Metode Naïve Bayes, Support Vector Machine dan Recurrent Neural Network pada Analisis Sentimen Ulasan Produk E-Commerce. Multitek Indonesia, Vol 17. 2023.

[14] Yunizar A, Rismawan T, Midyanti DM. Penerapan Metode Recurrent Neural Network Model Gated Recurrent Unit untuk Prediksi Harga Cryptocurrency. Jurnal Komputer dan Aplikasi, Vol 11 No 01. 2023.

[15] Kusuma NPN. Prediksi Harga Saham Blue Chip pada Indeks IDX30 menggunakan Algoritma Recurrent Neural Network. Jurnal Ekonomi Bisnis, Vol 23 No 1: 90-97. 2023.

[16] Selle N, Yudistira N, Dewi C. Perbandingan Prediksi Penggunaan Listrik dengan Menggunakan Metode Long Short Term Memory (LSTM) dan Recurrent Neural Network. Jurnal Teknologi Informasi dan Ilmu Komputer (JTIIK), Vol 9 No 1. 2022.

[17] Shiri Fm, Perumal T, Mustapha N, Mohamed R. A Comprehensive Overview and Comparative Analysis on Deep Learning Models. Journal on Artficial Intelligence, Vol 6 No 1:301-360. Researchegate. 2023.

[18] Rozi If, Wijayaningrum Vn, Khozin N. Klasifikasi Teks Laporan Masyarakat Pada Situs Lapor! Menggunakan Reccurent Neural Network. Jurnal Sistem Informasi (SISTEMASI), Vol 9 No 3. 2020.

[19] Pipin SJ, Purba R, Kurniawan H. Prediksi Saham Menggunakan Recurrent Neural Network (RNN-LSTM) dengan Optimasi Adaptive Moment Estimation. Journal of Computer System and Informatics (JoSYC), Vol 4 No 4. 2023.

[20] Samudra AG, Friska B, Kurnia M. Pengetahuan Tenaga Teknis Kefarmasian tentang Obat-obat Look-Alike Sound-Alike (LASA) di Apotek Kota Bengkulu. Benccolen Journal Of Pharmacy, Vol 2 No 1. 2022.

[21] Amrullah H. Pengaruh Pelatihan terhadap Penyimpanan LASA (Look Alike Sound Alike): Studi Kuasi Eksperimental. Babul Ilmi Jurnal Ilmiah Multi Science Kesehatan, Vol 14 no 2. 2022.

[22] Rika N, Rusmana WE. pengaruh Penyimpanan dan Penandaan Obat High Alert dan LASA (Look Alike Sound Alike) terhadap Risiko Terjadinya Human Error di salah satu Rumah Sakit Swasta Kota Bandung. JSTE, Vol 3 No 1. 2021.

[23] Zafirah AD, Junadi P. Studi Kasus: Pengaruh Penyimpanan dan Penandaan Obat High Alert dan LASA terhadap Resiko Terjadinya Human Error di Rumah Sakit khusus Mata Mencirim Tujuh Tujuh Medan. Jurnal Ilmiah Indonesia, Vol 7 No 9. 2022.

[24] Angraini D, Afriani T, Revina. Analisis Faktor-Faktor Terjadinya Medication Error di Apotek RSI Ibnu Sina Bukittinggi. Jurnal Endurance: Kajian Ilmiah Problema Kesehatan, Vol 6(1). 2021.

[25] Jabat DEBr, Sipayung LY, Dakhi KRS. Penerapan Algoritma Recurrent Neural Networks (RNN) untuk Klasifikasi Ulos Batak Toba. SNISTIK: Seminar Nasional Inovasi Sains Teknologi Informasi Komputer, Vol 1 No 2. 2024.