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# Probability Prediction for Graduate Admission Using CNN-LSTM Hybrid Algorithm

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**Abstract**

Currently, the prediction of student admissions still uses conventional machine learning algorithms where there is no algorithm for optimization. This study aims to produce a model that can predict student acceptance of ownership more optimally by using an optimization hybrid learning algorithm, namely the Convolutional Neural Network Long Short Term Memory (CNN-LSTM). This study uses the Microsoft Team Data Science Process method which consists of business understanding, data acquisition & understanding, modeling, and implementation as well as using the acceptance dataset obtained from the kaggle.com website as much as 500 data. The results showed that the CNN-LSTM hybrid learning model could optimize the prediction of students' chances of success in exposure as evidenced by the evaluation results of RMSE of 6.31%, MAE of 4.4%, and $R^2$ of 80.52%. This model is implemented in a website application using the Python language, the Django framework, and the MySQL database.

 

## A. Introduction

Acceptance of postgraduate students is one of the activities carried out by an institution to screen or select the best-qualified prospective students who meet the academic requirements set by the institution concerned [1]. On the student side, the goal of accepting postgraduate programs is to continue their education in postgraduate programs, namely to gain more specific and focused knowledge through academic pathways [2]. The postgraduate program itself is an educational level program that offers several study programs to scholarships that focus on developing expertise in a particular field [3]. To be accepted into the postgraduate program, students must meet several criteria and take an exam as a condition for registering for the postgraduate program [4]. Generally, institutions will select students based on Graduate Record Examination (GRE) scores, Test of English as a Foreign Language (TOEFL) scores, university ratings, statement of purpose assessments, letter of recommendation assessments, cumulative grade point average, and research experience [5].

A student's success in a postgraduate program can open up opportunities for deeper knowledge and skills and for obtaining an advanced degree related to an area of interest [6]. However, to achieve success in postgraduate admissions activities, several challenges must be faced by students. Generally, students will register themselves with institutions with accreditation levels, but many institutions accept students based on ratings based on Graduate Record Examination (GRE) scores, Test of English as a Foreign Language (TOEFL) scores, university ratings, statement of purpose assessments, letters of recommendation assessments, cumulative grade point average, and research experience [7]. So that students often experience problems, namely in selecting institutions that suit their profile and portfolio because most of them do not have information about the profiles and portfolios of other students which causes them to lack confidence in registering themselves at an institution [8]. On the other hand, currently there are only a few studies regarding the use of conventional machine learning algorithms to predict student acceptance by using the Linear Regression algorithm [9]–[11]. Thus, there has been no research on optimizing machine learning algorithms to more accurately and optimally predict postgraduate admissions.

Research that has been done previously related to the topic of postgraduate student admissions was carried out by Mohan S Acharya et al. [9] by comparing several machine learning algorithms and the best results are obtained, namely using the Linear Regression algorithm with an RMSE evaluation result of 6.92%, and $R^2$ of 72.48%. Then there is research by Mohd Aijaj Khan et al. [10] by comparing several machine learning algorithms and the best results are obtained, namely using the Linear Regression algorithm with an evaluation result of RMSE of 6.6%, MAE of 4.7%, and $R^2$ of 79.8%. Furthermore, there is research by Amal Al Ghamdi et al. [11] comparing several machine learning algorithms and the best results are obtained, namely using the Linear Regression algorithm with an RMSE evaluation result of 7.2%.

Therefore, to optimize the prediction of postgraduate student admissions, it is necessary to develop an optimization algorithm for predicting postgraduate student admissions to get more effective and efficient opportunities for student success rates in postgraduate admissions activities. Algorithm optimization is a process of increasing the performance and efficiency of an algorithm by making changes to the steps or structure of the algorithm compared to its competitiveness against conventional algorithms in solving optimization problems [12]. Algorithm optimization also involves selecting the right parameters, testing and comparing various approaches, and selecting the most suitable algorithm for the problem to be solved [13]. In predicting student admissions, this optimization is carried out to produce opportunities for student success based on data owned by a student. The predicted odds are based on data patterns that have previously been discovered and trained by the model. Thus, the developed model will be able to provide the most optimal percentage of opportunities that students might get in predicting postgraduate admissions.

Based on research on literature studies on the best optimization methods that can be used, the model developed utilizes the Hybrid Learning method with the Convolutional Neural Network Long Short Term Memory (CNN-LSTM) algorithm. Hybrid Learning is an approach that combines machine learning algorithms or deep learning algorithms in a balanced combination [14]. The aim is to harness the strengths and advantages of both approaches in solving complex data analysis problems to produce more accurate predictions of students' chances of succeeding in postgraduate courses. Convolutional Neural Network Long Short Term Memory (CNN-LSTM) is a type of architecture or approach in processing sequential data using neural networks. [15]. CNN-LSTM can study complex relationships between features in a data sequence and retain an understanding of the temporal context of the sequence. To find out the optimization performance of machine learning algorithms that have a good performance on the topic of graduate student admissions which are linear regression data, it can generally be measured using evaluation metrics such as RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), and $R^2$ (R- Squared) Score [16]. In this study, the confusion matrix was not used because according to previous research the target variable was in the form of opportunities which, when predictions were made after training, the predictions would have differences that could not be evaluated using the confusion matrix [9]–[11].

Research on optimizing algorithms using the CNN-LSTM hybrid model method has been carried out previously, namely regarding the optimization of water level predictions by Rahim Barzegar et al. [17] using the CNN-LSTM hybrid model and obtaining RMSE evaluation results of 3.5%, MAE of 2.6%, and $R^2$ of 99%. Then there is research on optimizing stock price predictions by Wanjie Lu et al. [18] using the CNN-LSTM hybrid model and obtaining RMSE evaluation results of 39.6%, MAE of 27.5%, and $R^2$ of 96.4%. Furthermore, there is research on optimizing residential energy consumption predictions by Tae-Young Kim et al. [19] using the CNN-LSTM hybrid model and obtaining RMSE evaluation results of 6.11% and MAE of 3.49%.

The implementation of the system built is in the form of a website-based application using the Python programming language. The programming language was chosen because it is ideal for developing artificial intelligence, machine learning, and deep learning projects [20]. Python has the advantage of being easy to develop website application tools because it has a very good level of code readability [21]. Then making a back-end on a website predicting graduate student acceptance using the Django framework and MySQL database. The Django Framework is a web framework that has a fast, efficient, and practical development framework to help easily create website-based applications because it uses the Python development language which can represent an Object Relational Mapper (ORM) [22]. So, when there is a change in the database, there is no need to make any more query adjustments. Then there is MySQL which is a database management system server program with Structured Query Language (SQL) commands that can send and receive data quickly, multi-threaded, and multi-user [23].

## B. Research Method

The research method used in this study is the Microsoft Team Data Science Process launched by Microsoft to provide predictive analytics solutions and applications efficiently [24]. This research method has a project cycle like CRISP-DM and includes four iterations, starting from business understanding, data acquisition & understanding, modeling, and deployment [25]. The stages of the research method can be seen in Figure 1.

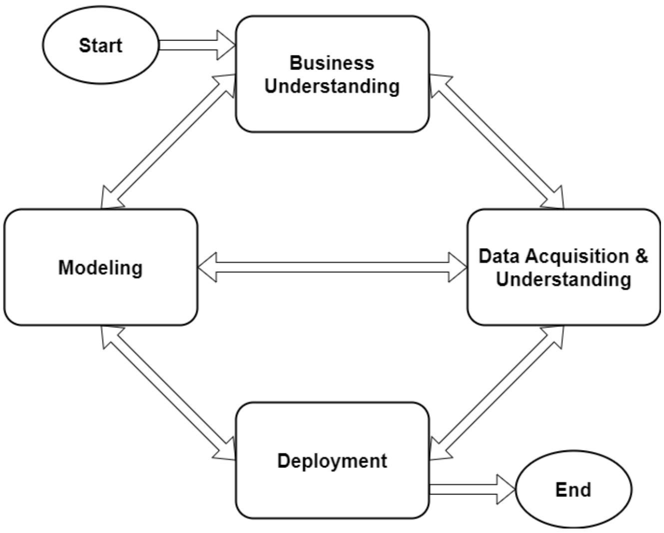


**Figure 1.** Stages of Research Methods

The explanation of each stage of the Microsoft Team Data Science Process research method used in this study is as follows:

A. Business Understanding
Business understanding involves a deep understanding of business problems and business goals to be achieved through data science projects. In this study, the identification of problems was carried out in the form of the absence of an algorithm to optimize the prediction of postgraduate student admissions which makes it easier for students to provide an overview of their chances of success in graduate student admissions. Thus, this study has the goal of optimizing predictions of postgraduate student admissions using the best algorithm based on previous research. Then to make it easier for users, especially students, to predict postgraduate admissions, the optimization result model will be implemented in a website application.

B. Data Acquisition & Understanding
Data acquisition & understanding involves collecting data relevant to a data science project and then understanding it in detail. Data understanding This

includes an understanding of data sources, data collection, data exploration such as an initial understanding of the characteristics and structure of data, as well as data cleaning. In this study, data was collected by collecting postgraduate admissions data on the kaggle.com data provider website which can be accessed via the following link https://www.kaggle.com/datasets/mohansacharya/graduate-admissions. The data retrieval is done by downloading the data to the local device. The data obtained in this study were 500 data and stored in a dataset file in CSV format. the data is stored in the MySQL database to make it easier when integrated with the application to be built. Then data exploration is carried out by examining detailed data information such as checking the number of data columns, number of data rows, data outliers, null value data, and correlation between columns in the dataset either through calculations or visualization. Based on the exploration of the data, it can be seen that the data is made for postgraduate admissions from an Indian perspective which may have limitations, namely having a scale of values that may be different. So that between an institution in a country may not be relevant to institution in another country. Furthermore, data cleaning is done by removing columns that are not needed or do not have a strong correlation with the target column, which in the dataset is the Chance of Admit column, namely the identifier column to improve model performance. The correlation of each column in the dataset can be seen in Figure 2. The columns that have the strongest correlation with the target column are by having values close to 1 and vice versa, the columns that have the weakest correlation with the target column are by having values that are close to the value 0. Here it can be seen that the CGPA column is the column with the strongest correlation and the Research Experience column is the column with the weakest correlation with the target or Chance of Admit column.

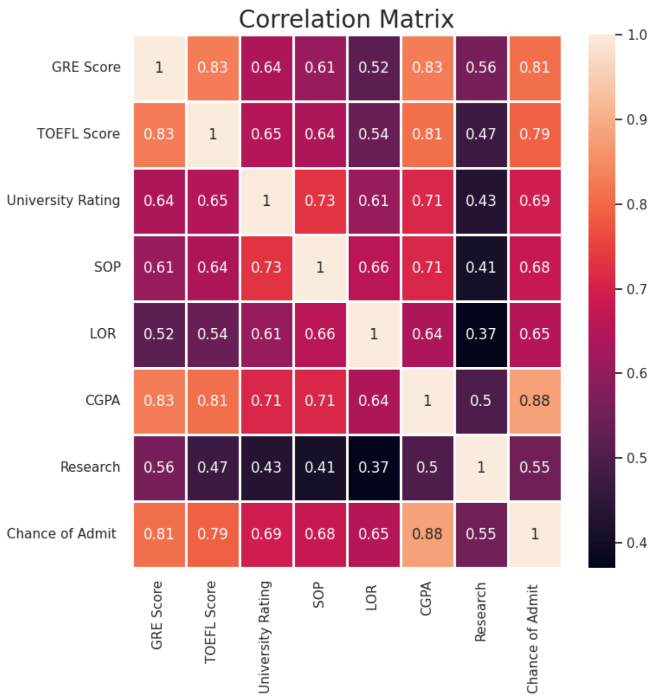


**Figure 2.** Correlation Between Columns in Dataset

C. Modeling

Modeling involves selecting appropriate models and algorithms to achieve the project's business objectives. Modeling also involves creating a model and training it using pre-processed data and evaluating the model. In this study, we selected data modeling using a hybrid algorithm, namely the Convolutional Neural Network Long Short Term Memory (CNN-LSTM) algorithm, which is the best algorithm for optimization based on previous research because it can overcome the problem of weakening gradients in machine learning algorithms and improve network capabilities in studying sequential relationships in data [26]. CNN-LSTM consists of two algorithms, namely CNN and LSTM they are sequenced sequentially which have advantages in feature extraction from data in data sequences by identifying these features and extracting relevant information using the convolution layer, while LSTM has advantages in processing sequential data that complex by learning data that must be lost or stored on each neuron [27]. This helps overcome the problem of weakening gradients and improves the network's ability to learn patterns or sequential relationships in data [28]. The architecture of the CNN-LSTM algorithm can be seen in Figure 3.

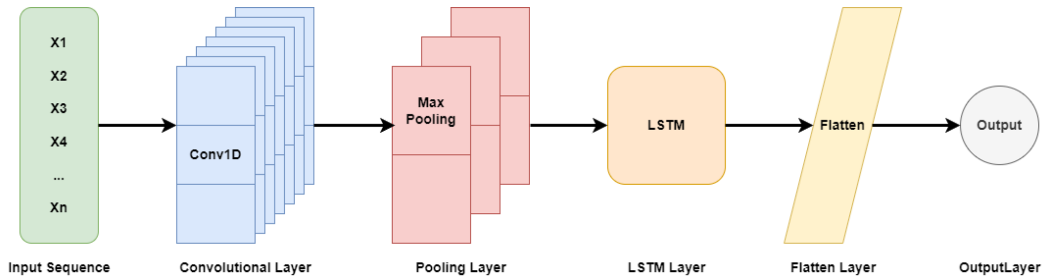


**Figure 3.** CNN-LSTM Algorithm Architecture

After modeling the data, evaluation is then carried out to measure the performance of the model that has been made. This evaluation is carried out to determine the performance of the model in predicting the new data entered. The evaluation method used is the evaluation metric for linear regression data Root Mean Squared Error (RMSE) which is used to measure the square root of the MSE and measures the prediction error in the same unit as the target variable, Mean Absolute Error (MAE) which is used to measure the average the average of the absolute difference between the value predicted by the model and the actual value of the target variable provided that the lower the MAE value, the better the model performance, R-Squared ($R^2$) is used to measure the extent to which the variation in the target variable can be explained by the model with the range conditions a value between 0 to 1 with a value of 1 indicates that the model perfectly explains the variability of the data [29].

The RMSE formula can be seen in Formula 1.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{yi} - \hat{y}i)^2} \quad (1)$$

The MAE formula can be seen in Formula 2.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\mathrm{yi} - \hat{y}i| \quad (2)$$

Formula $R^2$ can be seen in Formula 3.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\mathrm{yi}-\hat{y}i)^2}{\sum_{i=1}^{n}(\mathrm{yi}-\bar{\mathrm{y}})^2} \quad (3)$$

Information:
yi = actual value of target variable
ŷi = the value predicted by the model
ȳ = average value of the target variable
n = number of observations

D. Deployment

Deployment involves implementing the model in a production or further testing environment. The deployment includes integrating the model into existing systems, ensuring model performance, and preparing the necessary infrastructure. In this study, a deployment model was carried out on a website for predicting postgraduate acceptance that was built using the Python language and the Django framework. Then the implementation of the MySQL database was also carried out for storing the input data for new postgraduate admissions.

## C. Result and Discussion

The data for the research conducted were taken from the data provider website kaggle.com which can be accessed via the following link https://www.kaggle.com/datasets/mohansacharya/graduate-admissions. The data taken is in the form of tabular data stored in a CSV format file which is converted into a MySQL database. Based on the results of acquisition data, 500 lines of data were obtained which were then explored and cleaned of data on the Postgraduate Admissions dataset. The Postgraduate Admissions Dataset consists of 8 columns where 7 columns are features and 1 column is targets. The feature columns in the dataset include GRE, TOEFL, University Rating, SOP, LOR, CGPA, and Research Experience. As for the target column in the dataset, namely Chance of Admit. The explanation of the columns in the dataset is in Table 1.

**Table 1.** Columns in the Graduate Admissions Dataset

| No | Column Name | Description |
|---|---|---|
| 1 | GRE | The Graduate Record Examination (GRE) is a standardized test used to measure academic ability and potential for success in |

| | | |
|---|---|---|
| | | graduate studies in various fields. The GRE value scale in this dataset is 260 to 340. |
| 2 | TOEFL | The Test of English as a Foreign Language (TOEFL) is a standardized test designed to measure non-native English speakers who wish to study or work in an English-speaking environment. The TOEFL score scale in this dataset is 0 to 120. |
| 3 | University Rating | University rating is a rating or rating system used to evaluate and compare universities in various aspects. The University Rating scale on this dataset is 1 to 5. |
| 4 | SOP | A statement of purpose (SOP) is a personal piece of writing used as part of an application for further education at a college or university to consider prospective students. The SOP value scale in this dataset is 1 to 5. |
| 5 | LOR | A letter of recommendation (LOR) is a letter of recommendation written by an expert or an agency that knows prospective students well to support the application process by providing assessments and testimonials regarding the abilities of prospective students. The LOR value scale in this dataset is 1 to 5. |
| 6 | CGPA | Cumulative grade point average (CGPA) is the average cumulative grade point average as a measurement system used in many educational institutions to evaluate a student's academic achievement. The CGPA value scale in this dataset is 1 to 10. |
| 7 | *Research Experience* | Research experience is the experience one gain in conducting scientific research either in an academic environment, laboratory, or research institution. The Research Experience scale in this dataset is 1 for having conducted research and 0 for never having conducted research. |
| 8 | *Chance of Admit* | Chance of Admit is the result of the probability or opportunity for a prospective student to succeed in postgraduate admissions. The odds of being accepted are expressed as a percentage or a value between 0 and 1. |

Then the data that has been obtained is processed by converting it into an array form to facilitate the modeling stage using a 1-dimensional Convolutional Neural Network. The data that has been stored in the form of an array is then preprocessed so that the data can be processed during modeling. The data preprocessing process begins with data cleaning in the form of data standardization and data division into training data by 80% and data testing by 20%. Preprocessing is done so that the resulting model can produce good performance.

The data modeling stages were carried out using the Convolutional Neural Network Long Short Term Memory (CNN-LSTM) algorithm. Modeling the data with the CNN-LSTM algorithm has carried out several tests to find the best model parameters as shown in Table 2.

**Table 2.** Hyperparameter Tuning Testing

| No | Layer | Epoch | RMSE | MAE | $R^2$ |
|---|---|---|---|---|---|
| 1 | CNN-LSTM<br>CNN filters: 32<br>LSTM: 64 | 50 | 0.0657 | 0.0454 | 0.7887 |
| 2 | CNN-LSTM<br>CNN filters: 32<br>LSTM: 128 | 50 | 0.0674 | 0.0468 | 0.7772 |
| 3 | CNN-LSTM<br>CNN filters: 64<br>LSTM: 128 | 80 | 0.0653 | 0.0481 | 0.7908 |
| 4 | CNN-LSTM<br>CNN filters: 64<br>LSTM: 256 | 80 | 0.0631 | 0.0440 | 0.8052 |
| 5 | CNN-LSTM<br>CNN filters: 128<br>LSTM: 256 | 100 | 0.0663 | 0.0458 | 0.7848 |
| 6 | CNN-LSTM<br>CNN filters: 128<br>LSTM: 512 | 100 | 0.0661 | 0.0460 | 0.7860 |

Based on the test results in Table 2, the best model parameters were obtained using CNN-LSTM with 64 CNN filter layers, 256 LSTM layers, and 80 Epoch. Scripts for CNN-LSTM modeling can be seen in Figure 4.

```
# CNN-LSTM model
cnn_lstm_model = Sequential()
cnn_lstm_model.add(Conv1D(filters=64, kernel_size=3, activation='relu', input_shape=(X_train.shape[1], X_train.shape[2])))
cnn_lstm_model.add(MaxPooling1D(pool_size=2))
cnn_lstm_model.add(LSTM(256))
cnn_lstm_model.add(Flatten())
cnn_lstm_model.add(Dense(1))

# compile model
cnn_lstm_model.compile(optimizer='adam', loss='mean_squared_error')

# train model
history = cnn_lstm_model.fit(X_train, y_train, epochs=80, batch_size=32, validation_split=0.2, verbose=1)
```

**Figure 4.** Scripts Modeling CNN-LSTM

The layer structure in the model consists of a convolutional layer which is useful for feature extraction with convolution result features of 5 and the filters used are 64. Then the Max Pooling layer with the length of the features resulting from max pooling after dimension reduction is 2 and an indication of the number of channels available at the output is 64. Then the LSTM layer with the number of units or feature space dimensions at the LSTM output is 256. Then the Flatten layer with an indication of the length of a one-dimensional vector after flattening is 256. Then the Dense layer with an indication that the Dense layer produces output with one dimension, namely a vector with a length of 1. The layer structure of the model that has been made can be seen in Figure 5.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 5, 64)             256

 max_pooling1d (MaxPooling1D  (None, 2, 64)            0
 )

 lstm (LSTM)                 (None, 256)               328704

 flatten (Flatten)           (None, 256)               0

 dense (Dense)               (None, 1)                 257

=================================================================
Total params: 329,217
Trainable params: 329,217
Non-trainable params: 0
_________________________________________________________________
```

**Figure 5.** Model Layer Structure

Training on the model that has been made applies optimizer in the form of Adam and loss in the form of mean squared error. The model was trained using epochs of 80. The results of model training obtained an RMSE score of 0.0631 or 6.31%, an MAE score of 0.0440 or 4.4%, and an $R^2$ score of 0.8052 or 80.52%. The following is a graph of the loss results from the model training process which can be seen in Figure 6. The loss results during training are depicted with a blue line and the loss results during testing are depicted with orange lines that coincide and are directed close to 0 on the x-axis which indicates that the model has a very small loss or error.

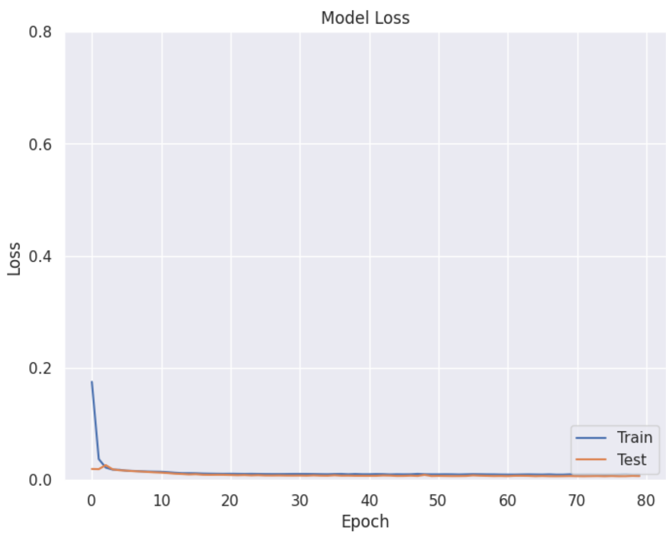


**Figure 6.** Graph of Training Loss Results

Then the graph of the model prediction results and actual data can be seen in Figure 7. Actual data is depicted with a blue line and predicted data is depicted with an orange line that almost coincides with the modeling process which indicates that the predicted data is suitable and the model can learn data patterns.

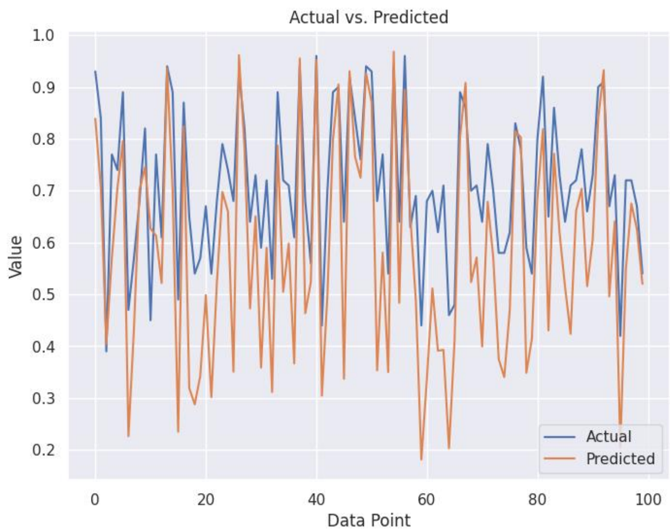


**Figure 7.** Graph of Model Prediction Results and Actual Data

After getting the results of the model training evaluation, a test is then carried out by predicting new postgraduate admissions data. Testing is done by inputting data and predicting the percentage of students' chances of success in postgraduate admissions. The probability results obtained have a very small difference from the actual data. This can happen because the prediction results will change along with the model's ability to learn and find new patterns from varied data [30]. The test results can be seen in Figure 8.

```
GRE Score: 337
TOEFL Score: 118
University Rating: 4
Statement of Purpose (SOP): 4.5
Letter of Recommendation (LOR): 4.5
CGPA: 9.65
Research Experience: 1
1/1 [==============================] - 0s 324ms/step

Prediksi Chance of Admit: 0.9596524238586426
```

**Figure 8.** Model Testing Results

The model that has been tested is then implemented in an application to facilitate the use of the postgraduate acceptance prediction model. Thus, users, especially students, can find out their chances of success in accepting postgraduate programs easily. The implementation implemented is in the form of a postgraduate admissions prediction website that has been integrated with the postgraduate admissions database. The graduate student acceptance prediction website was built using the Python language, the Django framework, and the MySQL database. Then on the display of website pages using HTML and CSS. The display of the postgraduate student acceptance prediction website that has been created can be seen in Figure 9.

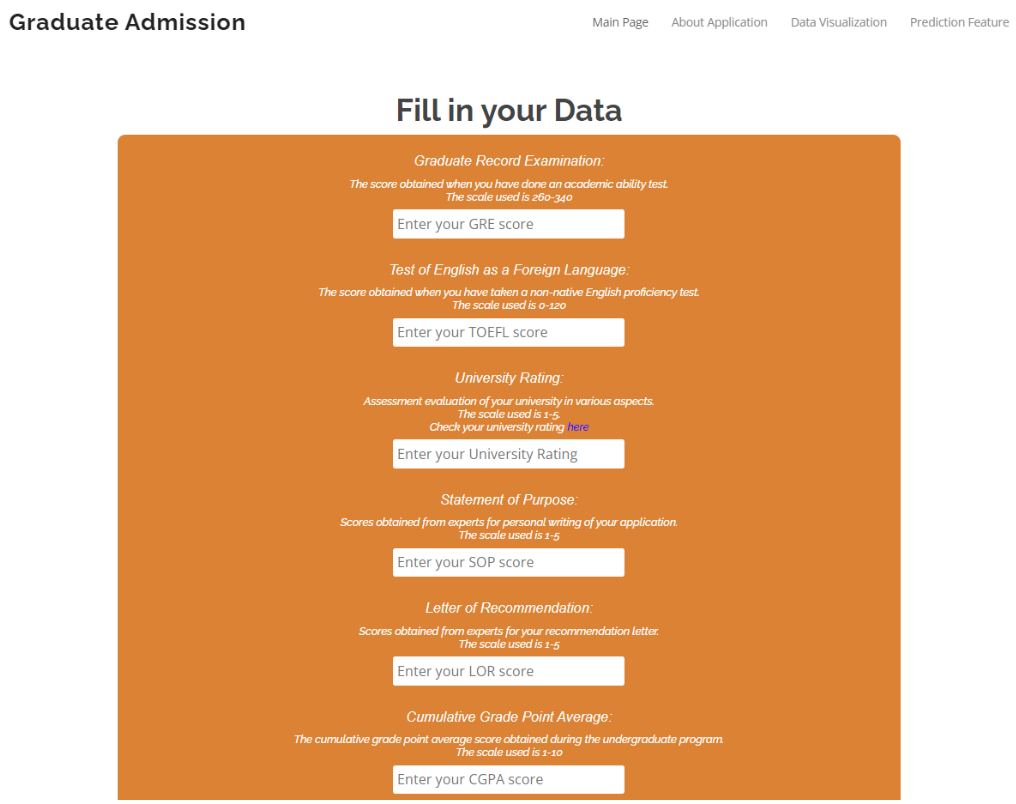


**Figure 9.** Website Display of Prediction of Postgraduate Student Admissions

The database that has been created consists of one table with a structure as in Table 3.

**Table 3.** Table Structure of Graduate Admissions Database

| # | Column Name | Data Type | Data Length |
|---|---|---|---|
| 1 | ID | Integer | 11 |
| 2 | TOEFL | Integer | 11 |
| 3 | GRE | Integer | 11 |
| 4 | Uiversity_Rating | Integer | 11 |
| 5 | SOP | Double | - |
| 6 | LOR | Double | - |
| 7 | CGPA | Double | - |
| 8 | Research_Experience | Tinyint | 1 |
| 9 | Chance_of_Admit | Float | - |

## D. Conclusion

Based on the research that has been done, the optimization of the algorithm for predicting postgraduate admissions has been successfully built and results in increased performance using the Convolutional Neural Network Long Short Term Memory (CNN-LSTM) hybrid algorithm compared to previous research. This can be proven by the results of the evaluation of the model which obtained an evaluation metric of RMSE of 6.31%, MAE of 4.4%, and $R^2$ of 80.52%. The model that has been created has been able to predict students' chances of success in the postgraduate admissions process well and has a very small difference from the actual data. However, the dataset used has limitations, namely having a scale of values that may differ from one agency to another. So that the model made from the dataset cannot predict data with different scales. Then, the model that has been made still has drawbacks, namely that in some dataset columns the data is gathered or centralized which causes the model to not optimally predict new data that is inputted outside of the data set and the new data will be categorized as outliers which will reduce the performance of the model in making predictions. Therefore, further research is needed to develop a prediction model for postgraduate student admissions so that it is more optimal, namely being able to produce appropriate predictions even though new input data from users is outside the data set contained in the dataset.

## E. References

[1] A. Iman and F. Wayne Xiaoguang Tian, “A Comparison of Classification Models in Predicting Graduate Admission Decision,” *Journal of Higher Education Theory and Practice*, vol. 21, no. 7, p. 219, 2021.

[2] A. Bag, “A Comparative Study of Regression Algorithms for Predicting Graduate Admission to a University,” *Research Gate*, 2020, doi: 10.13140/RG.2.2.13501.69605/1.

[3] A. Sulich, M. Rutkowska, and U. S. Singh, “Decision towards green careers and sustainable development,” in *Procedia Computer Science*, Elsevier B.V., 2021, pp. 2291–2300. doi: 10.1016/j.procs.2021.09.002.

[4] M. O. F. Goni, A. Matin, T. Hasan, M. A. I. Siddique, O. Jyoti, and F. M. S. Hasnain, “Graduate Admission Chance Prediction Using Deep Neural Network,” in *Proceedings of 2020 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering, WIECON-ECE 2020*, Institute of Electrical and Electronics Engineers Inc., Dec. 2020, pp. 259–262. doi: 10.1109/WIECON-ECE52138.2020.9397988.

[5] S. Jeganathan, S. Parthasarathy, A. R. Lakshminarayanan, P. M. Ashok Kumar, and M. K. A. Khan, “Predicting the post graduate admissions using classification techniques,” in *2021 International Conference on Emerging Smart Computing and Informatics, ESCI 2021*, Institute of Electrical and Electronics Engineers Inc., Mar. 2021, pp. 346–350. doi: 10.1109/ESCI50559.2021.9396815.

[6] V. Vo *et al.*, “Feature-based Learning for Diverse and Privacy-Preserving Counterfactual Explanations,” Sep. 2022, doi: 10.1145/3580305.3599343.

[7] P. Golden, K. Mojesh, L. M. Devarapalli, P. N. S. Reddy, S. Rajesh, and A. Chawla, “A Comparative Study on University Admission Predictions Using Machine Learning Techniques,” *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, pp. 537–548, Apr. 2021, doi: 10.32628/cseit2172107.

[8] F. He, J. Zhou, Z. Feng, G. Liu, and Y. Yang, “A hybrid short-term load forecasting model based on variational mode decomposition and long short-term memory networks considering relevant factors with Bayesian optimization

algorithm," *Appl Energy*, vol. 237, pp. 103–116, 2019, doi: https://doi.org/10.1016/j.apenergy.2019.01.055.

[9] Mohan S Acharya, Asfia Armaan, and Aneeta S Antony, "A Comparison of Regression Models for Prediction of Graduate Admissions," *Second International Conference on Computational Intelligence in Data Science (ICCIDS-2019)*, 2019.

[10] Mohd Aijaj Khan, Manish Dixit, and Aaradhya Dixit, "Demystifying and Anticipating Graduate School Admissions using Machine Learning Algorithms," 2020.

[11] A. Alghamdi, A. Barsheed, H. Almshjary, and H. Alghamdi, "A Machine Learning Approach for Graduate Admission Prediction," in *ACM International Conference Proceeding Series*, Association for Computing Machinery, Mar. 2020, pp. 155–158. doi: 10.1145/3388818.3393716.

[12] A. Faramarzi, M. Heidarinejad, B. Stephens, and S. Mirjalili, "Equilibrium optimizer: A novel optimization algorithm," *Knowl Based Syst*, vol. 191, p. 105190, 2020, doi: https://doi.org/10.1016/j.knosys.2019.105190.

[13] L. Abualigah, A. Diabat, S. Mirjalili, M. Abd Elaziz, and A. H. Gandomi, "The Arithmetic Optimization Algorithm," *Comput Methods Appl Mech Eng*, vol. 376, p. 113609, 2021, doi: https://doi.org/10.1016/j.cma.2020.113609.

[14] A. K. Dubey, "Optimized hybrid learning for multi disease prediction enabled by lion with butterfly optimization algorithm," *Sādhanā*, vol. 46, no. 2, p. 63, 2021, doi: 10.1007/s12046-021-01574-8.

[15] C. I. Garcia, F. Grasso, A. Luchetta, M. C. Piccirilli, L. Paolucci, and G. Talluri, "A comparison of power quality disturbance detection and classification methods using CNN, LSTM and CNN-LSTM," *Applied Sciences (Switzerland)*, vol. 10, no. 19, pp. 1–22, Oct. 2020, doi: 10.3390/app10196755.

[16] Doreswamy, H. K S, Y. KM, and I. Gad, "Forecasting Air Pollution Particulate Matter (PM2.5) Using Machine Learning Regression Models," *Procedia Comput Sci*, vol. 171, pp. 2057–2066, 2020, doi: https://doi.org/10.1016/j.procs.2020.04.221.

[17] R. Barzegar, M. T. Aalami, and J. Adamowski, "Coupling a hybrid CNN-LSTM deep learning model with a Boundary Corrected Maximal Overlap Discrete Wavelet Transform for multiscale Lake water level forecasting," *J Hydrol (Amst)*, vol. 598, p. 126196, 2021, doi: https://doi.org/10.1016/j.jhydrol.2021.126196.

[18] W. Lu, J. Li, Y. Li, A. Sun, and J. Wang, "A CNN-LSTM-based model to forecast stock prices," *Complexity*, vol. 2020, 2020, doi: 10.1155/2020/6622927.

[19] T.-Y. Kim and S.-B. Cho, "Predicting residential energy consumption using CNN-LSTM neural networks," *Energy*, vol. 182, pp. 72–81, 2019, doi: https://doi.org/10.1016/j.energy.2019.05.230.

[20] S. Raschka, J. Patterson, and C. Nolet, "Machine learning in python: Main developments and technology trends in data science, machine learning, and artificial intelligence," *Information (Switzerland)*, vol. 11, no. 4. MDPI AG, Apr. 01, 2020. doi: 10.3390/info11040193.

[21] A. Berti, S. J. van Zelst, and W. van der Aalst, "Process Mining for Python (PM4Py): Bridging the Gap Between Process- and Data Science," May 2019, [Online]. Available: http://arxiv.org/abs/1905.06169

[22] N. Idris, C. Feresa, M. Foozy, and P. Shamala, “A Generic Review of Web Technology: DJango and Flask,” 2020.
[23] S. Shah, Y. Patel, K. Panchal, P. Gandhi, P. Patel, and A. Desai, “Python and MySQL based Smart Digital Retail Management System,” in *2021 6th International Conference for Convergence in Technology (I2CT)*, 2021, pp. 1–6. doi: 10.1109/I2CT51068.2021.9417913.
[24] C. J. Costa and J. T. Aparicio, “POST-DS: A Methodology to Boost Data Science,” *2020 15th Iberian Conference on Information Systems and Technologies (CISTI)*, pp. 1–6, 2020, doi: 10.23919/CISTI49556.2020.9140932.
[25] A. K. Gupta, “Business Analytics: Process and Practical Applications,” in *Trends of Data Science and Applications: Theory and Practices*, S. S. Rautaray, P. Pemmaraju, and H. Mohanty, Eds., Singapore: Springer Singapore, 2021, pp. 307–326. doi: 10.1007/978-981-33-6815-6_15.
[26] X. Zhang, X. Lu, W. Li, and S. Wang, “Prediction of the remaining useful life of cutting tool using the Hurst exponent and CNN-LSTM,” *The International Journal of Advanced Manufacturing Technology*, vol. 112, no. 7, pp. 2277–2299, 2021, doi: 10.1007/s00170-020-06447-8.
[27] X. Jin, X. Yu, X. Wang, Y. Bai, T. Su, and J. Kong, “Prediction for Time Series with CNN and LSTM,” in *Proceedings of the 11th International Conference on Modelling, Identification and Control (ICMIC2019)*, R. Wang, Z. Chen, W. Zhang, and Q. Zhu, Eds., Singapore: Springer Singapore, 2020, pp. 631–641.
[28] G. Xie, A. Shangguan, R. Fei, W. Ji, W. Ma, and X. Hei, “Motion trajectory prediction based on a CNN-LSTM sequential model,” *Science China Information Sciences*, vol. 63, no. 11, p. 212207, 2020, doi: 10.1007/s11432-019-2761-y.
[29] G. An *et al.*, “Using machine learning for estimating rice chlorophyll content from in situ hyperspectral data,” *Remote Sens (Basel)*, vol. 12, no. 18, Sep. 2020, doi: 10.3390/RS12183104.
[30] Y. Hua, Z. Zhao, R. Li, X. Chen, Z. Liu, and H. Zhang, “Deep Learning with Long Short-Term Memory for Time Series Prediction,” *IEEE Communications Magazine*, vol. 57, no. 6, pp. 114–119, 2019, doi: 10.1109/MCOM.2019.1800155.