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Implementation of novel Machine Learning Technique using several Meta with Naive Bayes Models to Analyse the Performance of Wave Energy Converters

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ABSTRACT

Optimization of the layouts of arrays of wave energy converters (WECs) is a challenging problem. The hydrodynamic analysis and performance estimation of such systems are performed using semi-analytical and numerical models such as the boundary element method. However, the analysis of an array of such converters becomes computationally expensive, and the computational time increases rapidly with the number of devices in the system. As such determination of optimal layouts of WECs in arrays becomes extremely difficult. This paper explores the Ada Boost with Naïve Bayes perform well as well it showing an efficient outcome. It has the greatest accuracy result of 85.75%. The Ada Boost with Naïve Bayes produces the greatest precision result of 0.86. The Ada Boost with Naïve Bayes and Stochastic Gradient Boost with Naïve Bayes produce the maximum recall of 0.86. The Ada Boost with Naïve Bayes has the greatest F-Measure result of 0.86. The Ada Boost with Naïve Bayes model has the highest MCC value of 0.65. The Ada Boost with Naïve Bayes model has the greatest kappa value of 0.66. The Ada Boost with Naïve Bayes model has an optimal results compare with other models.

INTRODUCTION

This work introduces wave energy converters and power systems. [1]Energy demand will rise globally in the coming decades. Meanwhile, sustainable development and environmental protection must limit the energy industry's growth.[2] Oil shortages are inevitable. Renewable energy could help reduce energy industry carbon dioxide emissions. Such technologies are booming.[3,4] Europe leads wind energy with thousands of MW added in the last few years. Governments and industry are focused on offshore wind energy. This rapidly increasing field interacts favourably with some marine renewables, and combined offshore power plants to utilise more resources have been suggested. Wave energy, the most concentrated renewable energy source, may develop in the next years. It might produce high pressure for reverse osmosis, which could desalinate water on islands. Tidal streams, oceanic temperature and salinity gradients, and waves are other marine renewable energy sources. Most wave energy technologies require extensive R&D. Parallel technology and power electronics standardization have improved prospects since the 1970s (new converters can be cheaper and more reliable). Wave energy technology has reduced kWh production costs by one order of magnitude in the last 20 years. Many demonstration wave power plants have been developed (a few were full-size). Recently, some prototypes have proven their technology and may be suitable for pre-commercialization.

Ocean wave energy is a renewable energy source that could help meet global electricity demand. Concentrated solar energy has high short- and long-term variability. Well-built devices can transform sea wave energy into electricity by following numerous ideas and concepts. Systems must survive tremendous loads in storms. So, any cost-effective wave energy tapping strategy must balance efficiency and reliability, which presents technical hurdles.

What follows is the rest of the paper's outline: The associated work is described in Section 2. The proposed technique is introduced in Section 3, followed by a brief overview of the results and discussion in Section 4. In Section 5, we wrap up the paper and its findings.

II Literature Survey

Fossil fuels provide most energy [5]. Climate change and pollution are caused by non-renewable energy [6]. Low-carbon energy is essential. Non-petroleum energy sources have grown significantly. Solar, wind, tidal, and geothermal energy are most popular [7]. Wave energy is the second-most potential ocean renewable energy [8]. WECs generate power from ocean waves. WECs differ [9,10]. Investment and power management depend on reliable WEC forecasts. Investors worldwide need WEC system power generation potential predictions [11]. Numerical calculations and experiments using WEC system output power [12,13]. "Searaser," a breakthrough wave energy converter, was used in this study [14]. Ocean waves are affordable, safe, predictable, and clean. Large-scale integrated maritime energy systems are vulnerable to uncertainty [15,16]. Hence, accurate ocean wave energy estimates reduce power generation building costs and pilot programmes. Wave energy is abundant and predictable [7,18]. Engineers cannot predict ocean wave power from random data. Researchers wish to replace numerical solutions because solving equations with intricate boundary conditions is time-consuming and expensive. AI estimates energy system production capacity fast and affordably. Hence, engineering AI researchers have developed algorithms to predict ocean wave energy systems' electrical power from effective parameters [19,20]. Zhenqing et al. [21] predicted ocean waves using machine learning and genetic algorithms. Converters are shown using wave periods, wave height, and ocean depth. Tuning converters solved industrial technological concerns. Li et al. [22] examined wave power parameters. Machine learning and an artificial neural network predicted the wave's free surface height and force. Mistakes showed a power capture efficiency-parameter relationship. Gomez et al. [23] created a new software tool with a user-friendly guiding interface to predict output from two meteorological data sources using the latest machine learning methods. Butt et al. [24] introduced AI system forecasting. 24 h load prediction. These technologies improve maintenance by assessing error kinds. LSTM projected electricity demand by Cheng et al. [25]. LSTM improves forecasting by 21.80% and 28.57%. Lin et al. [26] improved LSTM error-based power prediction. LSTM yielded the best results. Deep learning projected wave energy converter power for Ni et al. High-frequency waves strongly affect modelling efficiency when comparing deep learning systems.

III Materials and Methods

The Dataset gathered from UCI's open data repository. Positions and absorbed power outputs from four actual wave scenarios off the southern coast of Australia make up this data set (Sydney, Adelaide, Perth and Tasmania). The CETO [1] model of totally submerged three-tether converter is used in this application. In a space-restricted setting, 16 WECs are strategically located. The issue is classified as a costly optimisation problem because the examination of each farm takes several minutes.

Features Information:

1. WECs position {X1, X2… X16; Y1, Y2… Y16} continuous from 0 to 566 (m).
2. WECs absorbed power: {P1, P2... P16}
3. Total power output of the farm: Powerall
4. Location: Perth, Adelaide, Sydney, and Tasmania

Methods:

The following method are applied in this research work

- Borrowed dataset
- Data preprocessing
- Apply for Ensemble machine learning algorithms:
- Gradient Boosting Machine with Naïve Bayes (GBM with NB)
- Stochastic Gradient Boosting with Naive Bayes(SGD with NB)
- AB with NB(Ada with NB)
- Extreme Gradient Boost with Naive Bayes(XGB with NB)
- Light Gradient Boosting Machine with Naive Bayes(LGBM with NB)
- To get Optimal results
- Find a best Model

To produce an efficient result, these strategies were applied in python API. This study uses only 10% of the total dataset and uses tenfold cross validation for all categories.

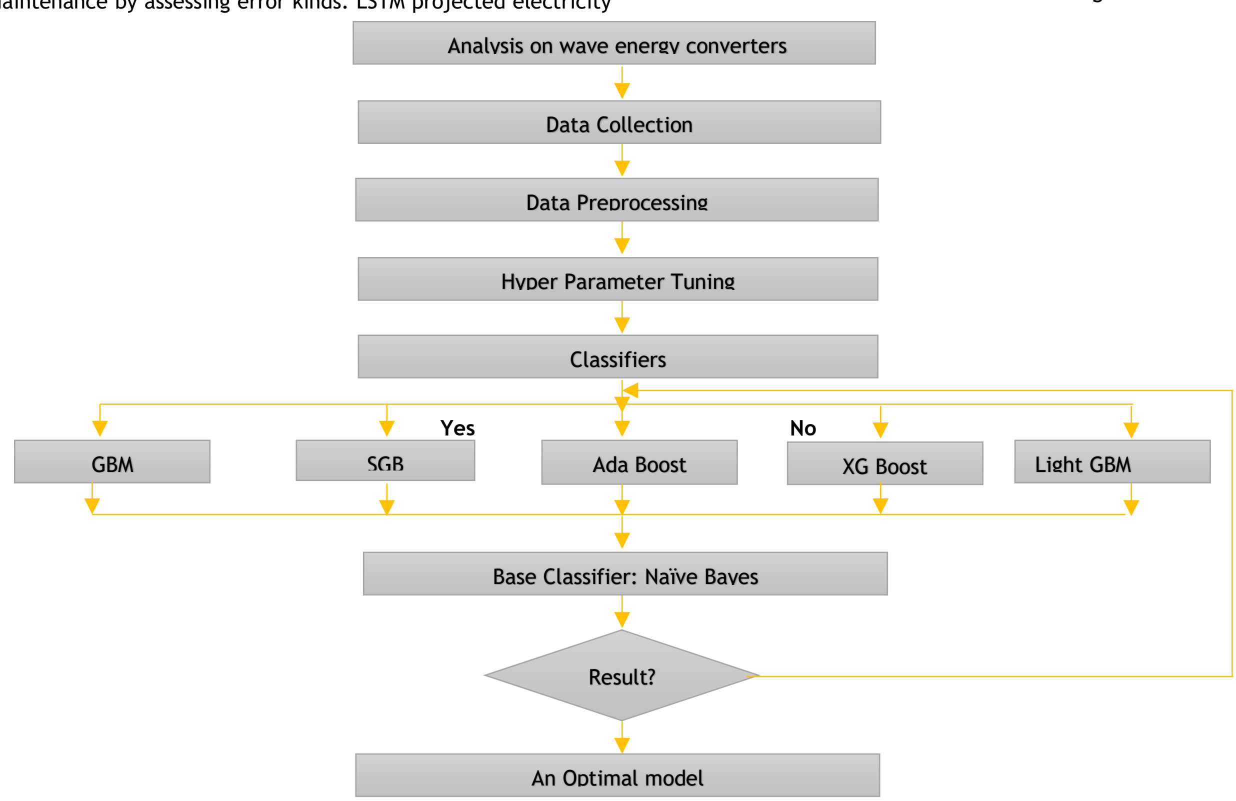

Figure 1: Proposed System

Table 2: Performance of selected classifiers

S.No	Classifiers	Accuracy	Precision	Recall	F-Measure	MCC	Kappa
1	AB with NB	85.75%	0.86	0.86	0.86	0.65	0.66
2	XGB with NB	84.10%	0.84	0.84	0.83	0.56	0.55
3	LGB with NB	83.85%	0.83	0.83	0.84	0.56	0.58
4	GDM with NB	79.02%	0.81	0.8	0.79	0.54	0.54
5	SGB with NB	85.00%	0.85	0.86	0.84	0.58	0.59

The above table shows that the various selected ensemble classifiers.
The AB with NB has an accuracy level of 85.75%, a precision value of 0.86, a recall value of 0.86, an F-Measure value of 0.86, an MCC value of 0.65 and a kappa statistic value of 0.66.
The XGB with NB results in an accuracy level of 84.10%, a precision value of 0.84, a recall value of 0.84, an F-Measure value of 0.83, an MCC value of 0.56 and a kappa statistic value of 0.55.
The LGBM with NB produces accuracy level 83.85%, a precision value 0.83, recall value 0.83, an F-Measure value 0.84,an MCC value 0.56 and a kappa statistic value 0.58.
The GBM with NB produces a yield of 79.02% an accuracy, a precision value of 0.81, a recall of 0.80, an F-Measure of 0.79, an MCC of 0.54 and a kappa statistic of 0.54.
The SGB with NB results in an accuracy level of 85%, a precision value of 0.86, a recall value of 0.86, an F-Measure value of 0.84,an MCC value of 0.58 and a kappa statistic value of 0.59.

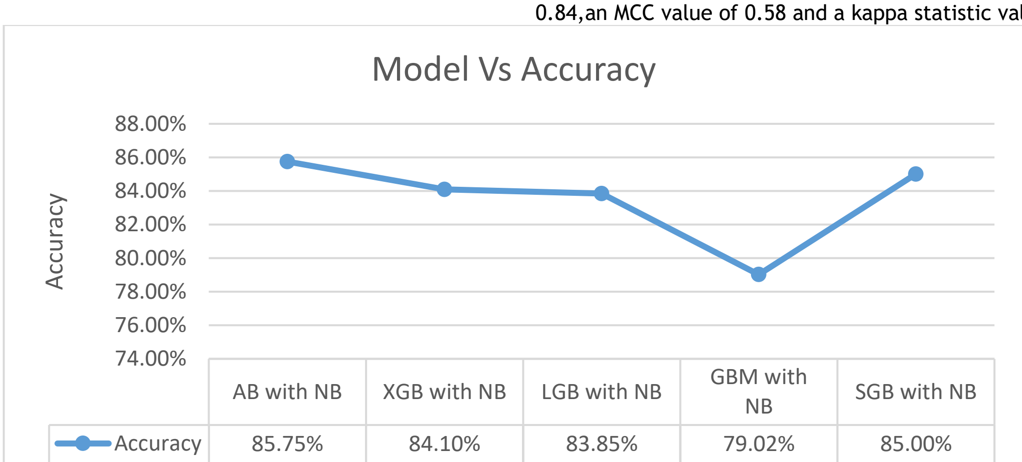

Figure 2: Performance of Ensemble classifiers with their accuracies

The above diagram shows that the accuracy performances of selected models. The AB with NB has the greatest accuracy result of 85.75%. The GBM with NB produces the lowest accuracy result of 79.02%. The accuracy of the LGBM with NB, XGB with NB, and SGB with NB is 83.85%, 84.10%, and 85%, respectively.

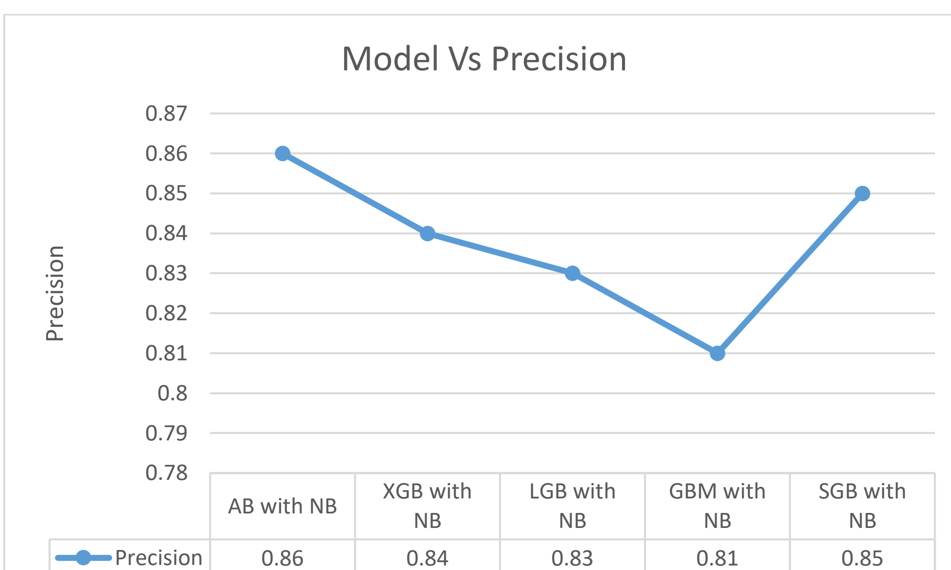

Figure 3: Performance of Ensemble Classifiers with their Precision values

The precision performances of selected models are depicted in the diagram above. The AB with NB produces the greatest precision result of 0.86. GBM with NB produces the lowest accuracy result of 0.81. The accuracy levels of the LGBM with NB, XGB with NB, and SGB with NB are 0.83, 0.84, and 0.85, respectively.

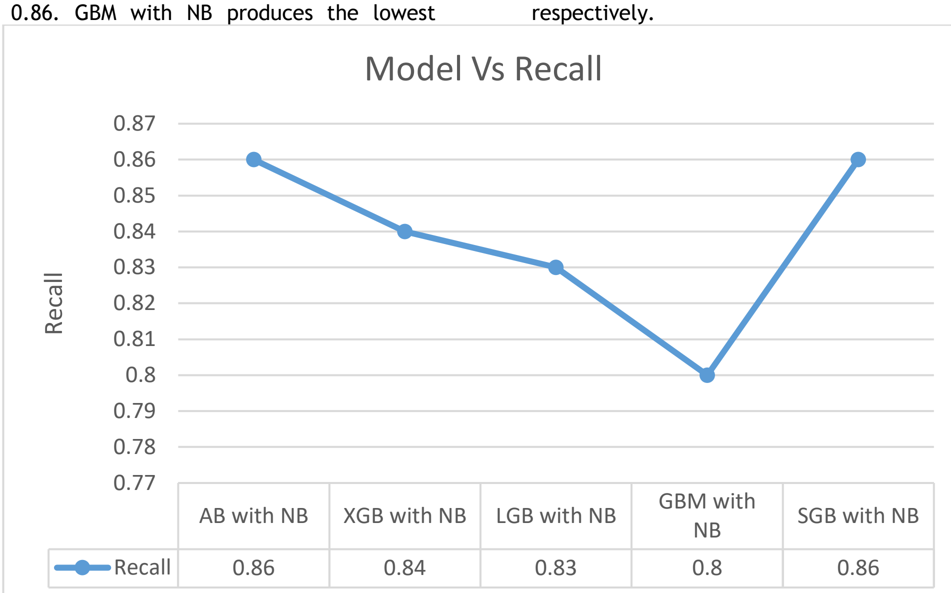

Figure 4: Performance of Ensemble Classifiers with their Recall values

The graph above depicts the recall performances of selected models. The AB with NB and SGB with NB produce the maximum recall of 0.86. GBM with NB produces the lowest recall result of 0.80. The recall levels for the LGBM with NB and the Extreme GBM with NB are 0.83 and 0.84, respectively.

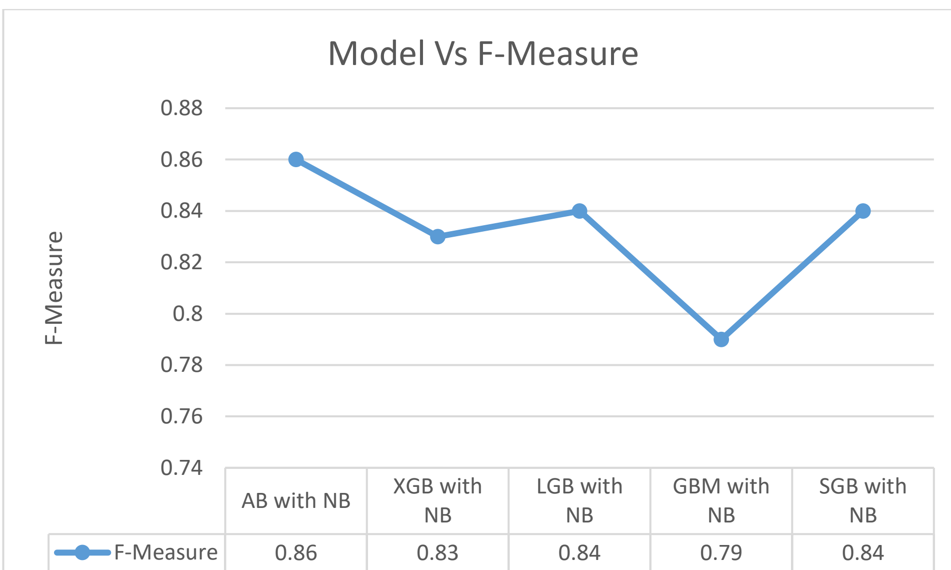

Figure 5: Performance of Ensemble Classifiers with their F-Measure values

The graph above depicts the F-Measure performances of selected models. The AB with NB has the greatest F-Measure result of 0.86. The GBM with NB produces the lowest F-Measure result of 0.79. The XGB with NB has an F-Measure of 0.83, whereas the LGB with NB and SGB with NB have the same value of 0.84.

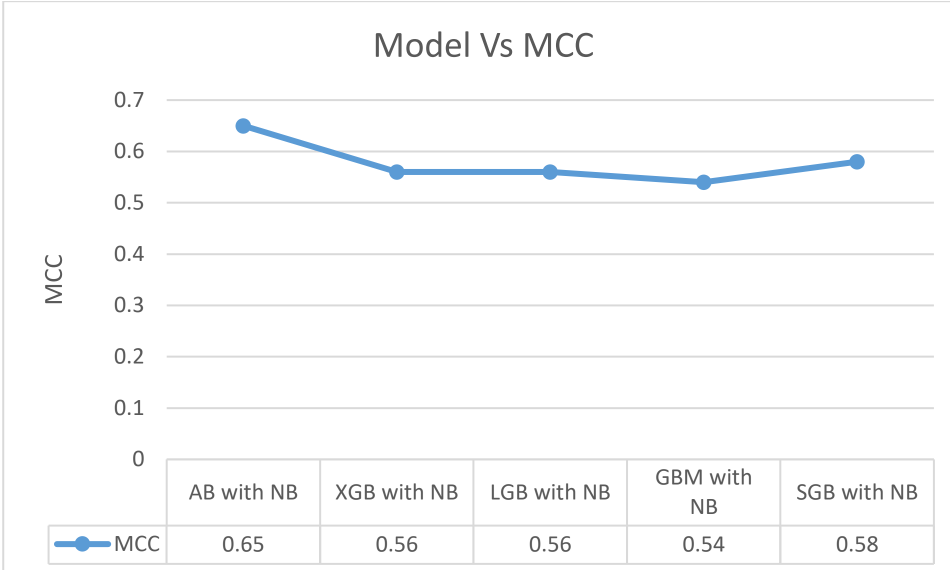

Figure 6: Performance of Ensemble Classifiers with their MCC values

The graphic above depicts the MCC performance of selected models. The AB with NB model has the highest MCC value of 0.65. GBM with NB produces the lowest MCC result (0.54). The remainder of the models, such as the XGB with NB model and the Light Gradient Boosting Machine with NB Decision Trees model, have the same MCC value of 0.56. The MCC value for SGB with NB 0.58.

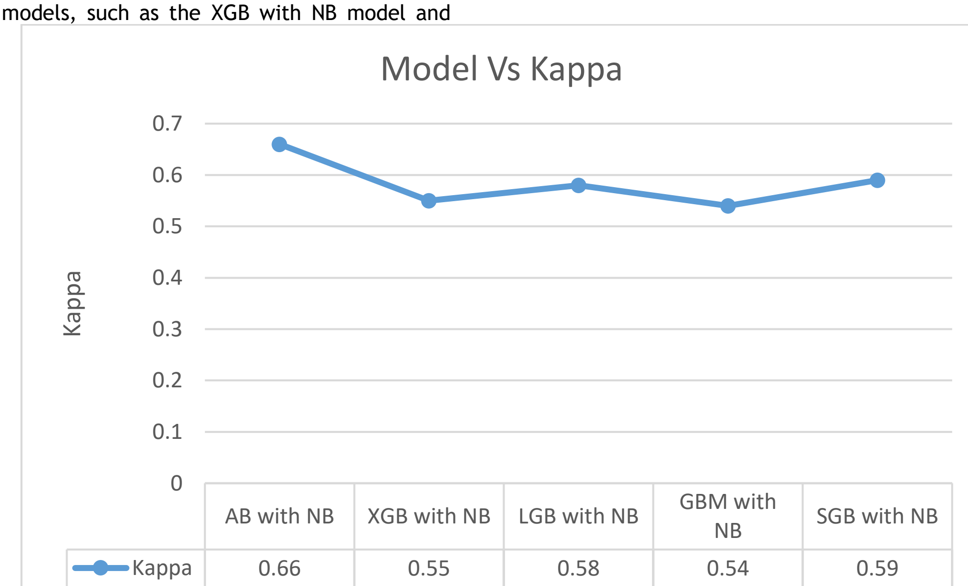

Figure 7: Performance of Ensemble classifiers with their Kappa statistic values

The graph above depicts the kappa value performances of selected models. The AB with NB model has the greatest kappa value of 0.66. The GBM with NB produces the lowest kappa result of 0.54. Other models with kappa values between 0.55 and 0.59 are Extreme Gradient Boost with NB, Light Gradient Boosting Machine with NB, and Stochastic Gradient Boosting with NB.

CONCLUSION

This work finds that the AB with NB has an F-Measure of 0.86, an MCC of 0.65, a kappa statistic of 0.66, a recall of 0.86, a precision of 0.86, and a precision of 0.86. The combined XGB and NB achieves an impressive 84.10% accuracy, 0.84 precision, 0.84 recall, 0.83 F-Measure, 0.56 MCC, and 0.55 kappa statistic. Accuracy of 83.85%, precision of 0.83%, recall of 0.83%, F-Measure of 0.84%, mean correlation coefficient of 0.56%, and kappa statistic of 0.58% are all generated by the LGBM with NB. Using NB, the GBM achieves a return of 79.02% accurate predictions, 0.81 precision, 0.80 recall, 0.79 F-Measure, 0.54 MCC, and 0.54 kappa. Accuracy is at 85%, precision is 0.86, recall is 0.86, the F-Measure is 0.84, the MCC is 0.58, and the kappa statistic is 0.59 when using the SGB with NB. The AB with NB has the greatest accuracy result of 85.75%. a precision result of 0.86, a recall of 0.86, an F-Measure result of 0.86, an MCC value of 0.65 and a kappa value of 0.66.This model recommends the AB with NB compare with other models.

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