JOURNAL OF DATA SCIENCE | Vol.2024:55
eISSN:2805-5160

# Comparison of ELM, LSTM, and CNN Models in Breast Cancer Classification

Silvia Ratna[1], M. Muflih[2], Haldi Budiman[3], Usman Syapotro[4], Muhammad Hamdani[5]

[1,2,3,4,5,6]Faculty of Information Technology, Islamic University of Kalimantan Muhammad Arsyad Al-Banjari, Indonesia

**Email:** silvia.ratna@uniska-bjm.ac.id[1], mmuflihfti@uniska-bjm.ac.id[2], haldibudiman@uniska-bjm.ac.id[3], 05usman.syapotro.study@gmail.com[4], mhdhamdani.formal@gmail.com[5]

## Abstract

Classification can significantly impact treatment decisions and patient outcomes. This study evaluates and compares the performance of three machine learning models Extreme Learning Machine (ELM), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) in breast cancer classification. ELM, known for its fast-learning speed and strong generalization, is compared with LSTM, which is effective in capturing long-term dependencies in sequential data, and CNN, which is renowned for its ability to automatically extract features from images and structured data. The models were trained and tested on a breast cancer dataset, focusing on accuracy and computational efficiency. The results revealed that while CNNs demonstrated better accuracy in feature-rich data, LSTMs excelled in handling sequential data patterns. On the other hand, ELM offers a good balance between training speed and classification performance. This comparative analysis provides valuable insights into the strengths and limitations of each model, contributing to the development of more effective breast cancer diagnostic tools. In this case, LSTM outperformed ELM by 0.91%, outperformed CNN significantly by 3.72%, and outperformed Improved LSTM by 0.91%. This indicate that the LSTM model shows higher accuracy in breast cancer classification.

## Keywords

Breast Cancer Classification, Comparison, Extreme Learning Machine (ELM), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN)

## Introduction

Breast cancer is one of the most prevalent cancers among women worldwide, and early detection plays a critical role in improving patient survival rates. Advances in technology and data processing methods have opened new avenues for enhancing the accuracy of breast cancer diagnosis and classification. One promising approach is the application of machine learning, which can analyze data more quickly and efficiently. These technologies not only assist in early detection but also offer more precise treatment recommendations based on the classification outcomes.

Several machine learning methods have previously been applied to breast cancer classification. Models such as Support Vector Machines (SVM), Decision Trees, and Random Forests have been widely used with varying degrees of accuracy. However, a key challenge in

**Submission**: 22 October 2024; **Acceptance:** 23 November 2024

applying machine learning to medical diagnosis is identifying models that not only provide high accuracy but are also efficient in terms of training time and computational resources. Traditional models often face limitations such as extended training times or insufficient robustness when dealing with complex datasets.

In recent years, advanced models like Extreme Learning Machine (ELM), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) have been introduced for medical classification tasks. ELM is known for its fast training speed and strong generalization capabilities, making it a suitable candidate for real-time applications. LSTM, on the other hand, excels at handling sequential data, which is useful for predicting temporal patterns in patient medical records. CNNs, with their ability to automatically extract features from both images and structured data, offer a powerful approach for managing feature-rich data, such as medical images.

This study aims to evaluate and compare the performance of three modern machine learning models ELM, LSTM, and CNN in breast cancer classification. By exploring the strengths of each model in terms of classification accuracy and computational efficiency, this research provides valuable insights into how machine learning technologies can be further developed to create more effective diagnostic tools for breast cancer. Additionally, the study highlights the suitability of each model depending on the specific characteristics of the data being analyzed.

## Methodology

This study evaluates the performance of ELM, LSTM, CNN, and Improved LSTM (LSTM with early stopping) on breast cancer datasets. ELM uses one hidden layer, LSTM has two layers, and CNN consists of convolution, pooling, and fully connected layers. The models were trained and tested with an 80-20 data split, and accuracy was used as the main evaluation metric, with an additional focus on the stability of Improved LSTM training.

### ELM

(Huang, 2015) Extreme Learning Machine (ELM) is a feedforward artificial neural network model with one hidden layer. ELM has a very fast learning speed and good generalization ability because the hidden layer input weights and biases are randomly selected and do not need to be tuned during the learning process.

### LSTM

(Li & Wu, 2015) LSTMs are an invaluable tool in sequential modeling, and their ability to capture long-term dependencies has revolutionized many fields, including speech recognition. Ongoing research continues to push the boundaries of LSTM, promising further advances in our ability to understand and process complex sequential data.

(Lee et al., 2017) LSTM is a very powerful and versatile tool for sequential modeling, and has made significant contributions to advancements in various fields, including speech recognition. Its ability to capture long-term dependencies and learn complex representations of sequential data makes it an invaluable tool in real-world applications.

**CNN**

(Zhang et al., 2020) Convolutional Neural Network (CNN) is a deep learning model inspired by the visual cortex of the brain, highly effective for processing image data. CNNs automatically learn important features of images through convolutional and pooling layers, enabling accurate pattern recognition and object detection. Its computationally efficient architecture and ability to learn high-level representations make it an invaluable tool in a variety of applications, although it has limitations in capturing temporal information directly.

**Improved LSTM**

(Abbasimehr & Paki, 2022) Improved LSTM is an improved LSTM architecture by adding projection layers and stacking multiple LSTM layers. These improvements allow the model to be more computationally efficient, especially when handling large models, and also improve the generalization ability of the model by reducing overfitting. This results in better performance in tasks such as large-scale speech recognition, where the improved LSTM can learn more complex and abstract representations of data, and avoid overfitting on training data.

## Result and Discussion

Table 1. Clasification Result

| Algorithm | Splitting Dataset | Accuracy |
|---|---|---|
| ELM | 80% Train, 20% Test | 0.9736 |
| LSTM | 80% Train, 20% Test | 0.9825 |
| CNN | 80% Train, 20% Test | 0.9473 |
| **Improved LSTM** | **80% Train, 20% Test** | **0.9737** |

The LSTM model showed the highest accuracy of 0.9825 and excelled in handling sequential data patterns, while the ELM known for its training speed recorded a very close accuracy of 0.9736, making it a good choice for real-time applications. While CNN is generally strong in extracting features from rich data such as medical images, in this study its accuracy was lower at 0.9473. Overall, LSTM excels in accuracy, ELM offers a balance between training speed and performance, and CNN remains relevant for feature-rich data, although not as accurate as the other models.

The Extreme Learning Machine (ELM) implemented using MLPClassifier with one hidden layer (100 neurons) showed a high accuracy of 97.36%. The model is fast and efficient, using Adam's solver and ReLU activation function, making it a strong choice for classification of non-linear data such as the breast cancer dataset.

Long Short-Term Memory (LSTM), designed for sequential data, produced a high accuracy of 97.37% even though the dataset was not sequential. With two layers of LSTM and dropout to prevent overfitting, the model is able to learn patterns well.

Convolutional Neural Network (CNN) using two layers of convolution and pooling, achieved 94.74% accuracy. CNN usually excels in spatial data, but in a breast cancer dataset that does not have a significant spatial dimension, its performance slightly lags behind other models.

Improved LSTM uses two LSTM layers, dropout, and early stopping to prevent overfitting. With an accuracy of 97.37%, this model improves the training stability, maintaining optimal performance without overfitting.

The conclusion from the accuracy comparison shows that Improved LSTM gives the same highest accuracy as ELM and LSTM, which is 97.37%, but with better training stability thanks to the use of dropout and early stopping. Compared to CNN which yielded a lower accuracy of 94.74%, Improved LSTM was superior in handling the breast cancer dataset, even though the dataset was not sequential. This makes Improved LSTM a more reliable choice in preventing overfitting and maintaining optimal performance, compared to the other models tested.

## Conclusion

In conclusion, it is shown that in this case base LSTM is adequate to achieve a high accuracy of 98.25%, better than Improved LSTM that achieve a slightly lower accuracy of 97.37%. This is may due to the fact that Improved LSTM is a model that are too complex for the presented data. This conclusion also takes the fact that there's too little data presented, making the data not complex enough for the Improved LSTM to capture the details adequately. Compared to other baseline model in this research such as ELM and CNN, LSTM generally performs better. With base LSTM performed better by 0.91% and 3.71% against ELM and CNN respectively. While Improved LSTM shown a minuscule improvement of 0.0102% over ELM, and an improvement by 2.78% over CNN.

## Recommendation

Future research could explore alternative methods, such as utilizing a larger dataset, applying feature engineering, experimenting with different models, or employing techniques like stacking and boosting, to achieve better results.

**References**

Abbasimehr, H., & Paki, R. (2022). Improving time series forecasting using LSTM and attention models. *Journal of Ambient Intelligence and Humanized Computing*, *13*(1), 673–691. https://doi.org/10.1007/s12652-020-02761-x

Bai, S., Kolter, J. Z., & Koltun, V. (2019). An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling. *arXiv preprint arXiv:1803.01271*. https://doi.org/10.48550/arXiv.1803.01271

Chen, J., Zhou, Z., Li, Y., & Xiao, F. (2021). Energy consumption forecasting using LSTM and graph-based attention mechanisms for demand response in smart grids. *Energy, 232*, 120917. https://doi.org/10.1016/j.energy.2021.120917

Huang, G. Bin. (2015). What are Extreme Learning Machines? Filling the Gap Between Frank Rosenblatt's Dream and John von Neumann's Puzzle. *Cognitive Computation*, *7*(3), 263–278. https://doi.org/10.1007/s12559-015-9333-0

Lee, D., Lim, M., Park, H., Kang, Y., Park, J. S., Jang, G. J., & Kim, J. H. (2017). Long short-term memory recurrent neural network-based acoustic model using connectionist temporal classification on a large-scale training corpus. *China Communications*, *14*(9), 23–31. https://doi.org/10.1109/CC.2017.8068761

Li, X., & Wu, X. (2015). Long short-term memory based convolutional recurrent neural networks for large vocabulary speech recognition. *Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH*, *2015-Janua*, 3219–3223. https://doi.org/10.21437/interspeech.2015-648

Song, H., Gao, Z., Xu, J., & Liang, X. (2020). Spatiotemporal Attention Mechanism for Multi-step Wind Power Forecasting. *IEEE Transactions on Sustainable Energy, 11*(4), 2211–2220. https://doi.org/10.1109/TSTE.2020.2969623

Zhang, R., Chen, P., & Xie, H. (2020). Time-series prediction of multi-horizon traffic flow based on attention mechanism and LSTM encoder-decoder. *Transportation Research Part C: Emerging Technologies, 120*, 102762. https://doi.org/10.1016/j.trc.2020.102762

Zhang, Y., Soon, H. G., Ye, D., Fuh, J. Y. H., & Zhu, K. (2020). Powder-Bed Fusion Process Monitoring by Machine Vision with Hybrid Convolutional Neural Networks. *IEEE Transactions on Industrial Informatics*, *16*(9), 5769–5779. https://doi.org/10.1109/TII.2019.2956078

Zhang, Y., Wang, S., Zhu, K., & Liu, Y. (2021). Hybrid deep learning models for air quality forecasting using LSTM and attention mechanism. *Journal of Cleaner Production, 297*, 126630. https://doi.org/10.1016/j.jclepro.2021.126630