



Mahidol University
Wisdom of the Land

Machine Learning vs Logistic Regression

Sharmin Akter

6336641

Content

- Limitations of Logistic Regression
- Benefits of Machine Learning in Binary Classification
- Machine learning for Multiclass Classification

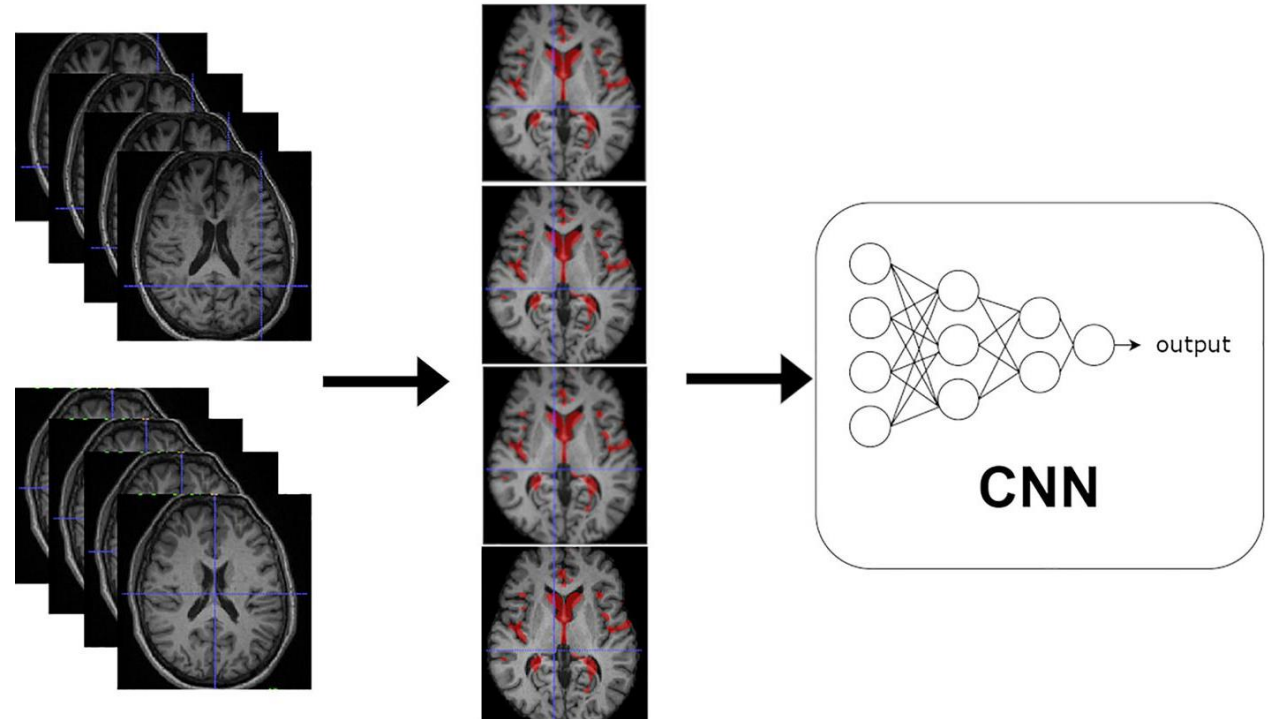
Limitations of Logistic Regression

1. Only does binary classification while machine learning can do multiclass
2. Complex nonlinear relationships
3. High-dimensional data
4. Can't handle imbalanced data
5. Complex image and text classification becomes difficult as it lack of automatic feature selection

Benefits of Machine Learning in Binary Classification

1. Image Classification:

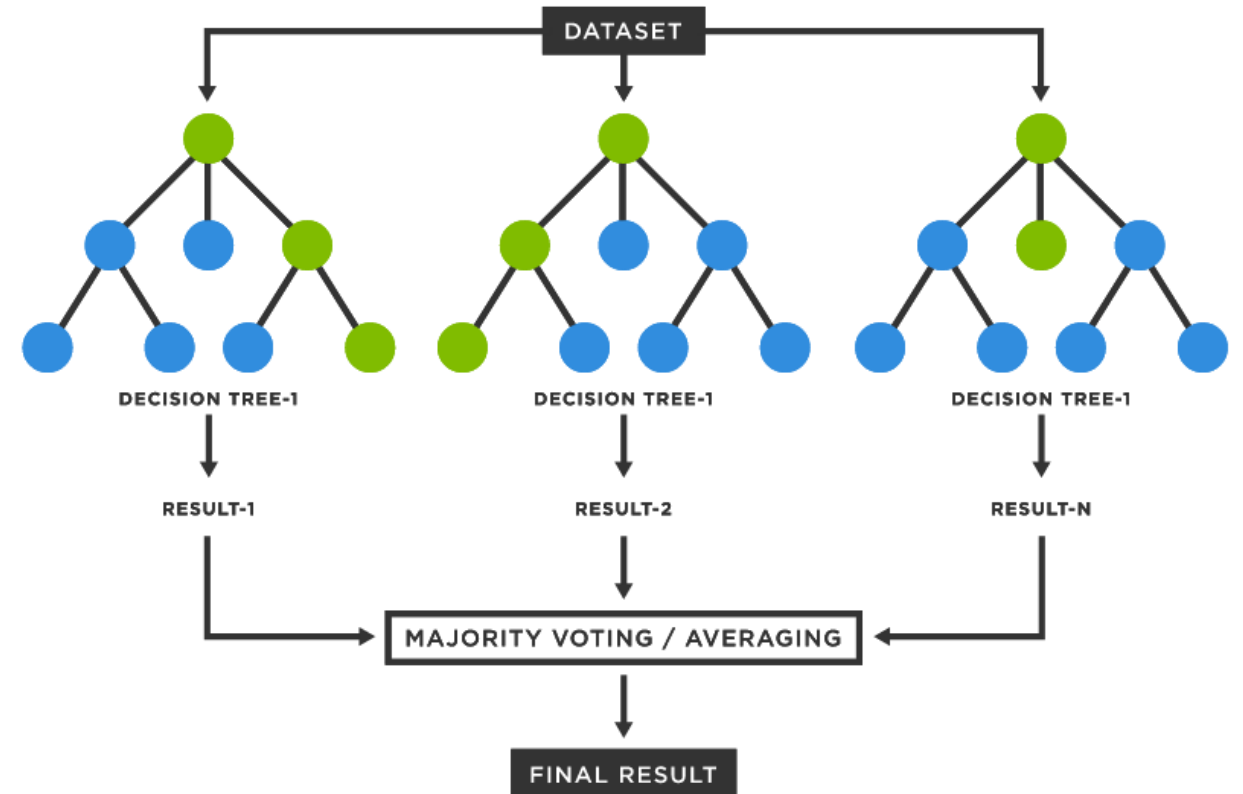
Convolutional Neural Networks (CNNs) have demonstrated remarkable success in image classification tasks compared to logistic regression. CNNs can capture complex spatial relationships in images and automatically learn hierarchical representations, leading to improved classification accuracy.



Benefits of Machine Learning in Binary Classification

3. Multiple outcomes / Multiclass:

Machine learning algorithms, such as random forests and gradient boosting, have better performance multiclass classification than logistic regression. These algorithms can effectively handle imbalanced datasets, capture complex patterns, and provide better predictive power.

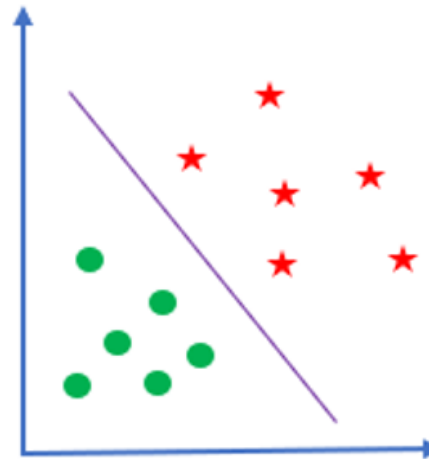


Benefits of Machine Learning in Binary Classification

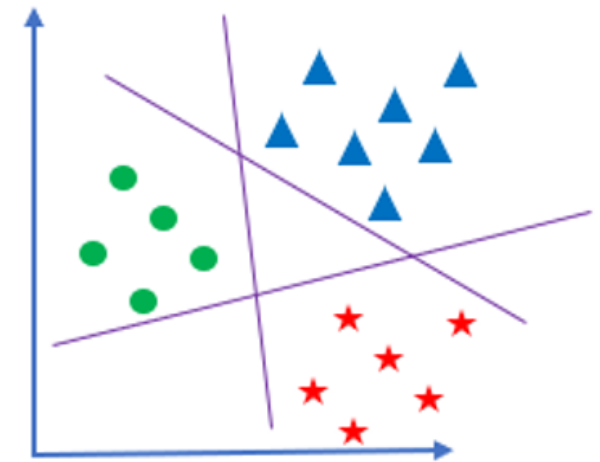
4. Health Diagnosis:

Machine learning algorithms, including support vector machines (SVMs) and ensemble methods like AdaBoost, have outperformed logistic regression in health diagnosis tasks, such as predicting diseases or identifying risk factors. These algorithms can handle complex interactions between predictors and provide improved predictive accuracy.

Binary classification



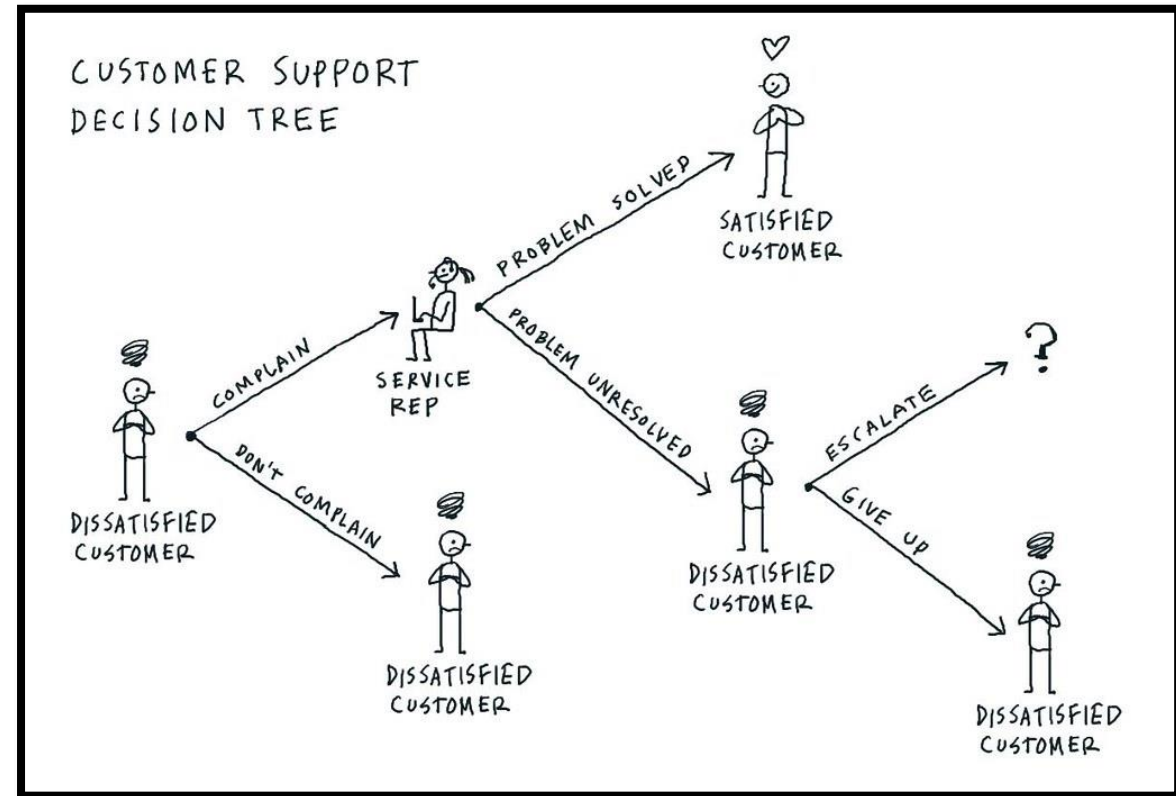
Multi-class classification



Benefits of Machine Learning in Binary Classification

5. Customer Churn Prediction:

Various machine learning algorithms, including decision trees, random forests, and gradient boosting, have demonstrated better performance than logistic regression in customer churn prediction. These algorithms can capture nonlinear relationships, handle high-dimensional data, and improve the predictive accuracy.



Reference

- Breiman, L. (2001). Statistical modeling: The two cultures. *Statistical Science*, 16(3), 199-231.
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). Springer. (Chapter 3)
- Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, 16, 321-357.
- Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, 61, 85-117.
- LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436-444.
- Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. In *Advances in neural information processing systems* (pp. 1097-1105).
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is all you need. In *Advances in neural information processing systems* (pp. 5998-6008).
- Dal Pozzolo, A., Caelen, O., Johnson, R. A., & Bontempi, G. (2015). Calibrating probability with undersampling for unbalanced classification. In *Symposium on Computational Intelligence and Data Mining (CIDM)* (pp. 159-166).
- Pham, T., Tran, T., Phung, D., Venkatesh, S., & Berk, M. (2017). Temporal regularized matrix factorization for high-dimensional time series prediction. In *International Conference on Data Mining (ICDM)* (pp. 785-790).
- Verbeke, W., Dejaeger, K., Martens, D., Hurley, N., & Baesens, B. (2012). New insights into churn prediction in the telecommunication sector: A profit driven data mining approach. *European Journal of Operational Research*, 218(1), 211-229.