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**Provision of 5G Network Services with High Efficiency using Artificial Neural Network (ANN) Algorithm in Comparison with Decision Tree Algorithm**

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**Keywords:** Efficiency, 5G Network Services,  Artificial Neural Network (ANN),  Decision Tree Algorithm, Comparison

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**ABSTRACT**

In this study, we investigate Efficiency Enhancement of 5G Network Services using Artificial Neural Network (ANN) Algorithm in Comparison with Decision Tree  Algorithm. The focus lies on enhancing the detection of fraudulent services through a novel approach employing Artificial Neural Network, juxtaposed with the traditional Decision Tree   method. **Materials and Methods:** To Encompass a comparison between the two algorithms: Artificial Neural Network and Decision Tree  . A dataset comprising 1784 samples was subjected to statistical analysis, with 1200 samples allocated for model training and 584 for testing. Utilizing the Clincalc tool with a G power setting of 85% parameters and alpha=0.05, alongside a power=0.85, the sample size for predicting fraudulent service enrollment websites was fixed at N=10 for each group, with a confidence interval of 95%. **Results:** indicate a statistically significant difference (p=0.000, p<0.05) necessary for identifying fraudulent websites. The novel Artificial Neural Network approach demonstrates superior performance, achieving an accuracy of 71.40% compared to 37.15% attained by Decision Tree  .(Independent sample t-test). **Conclusion:** The accuracy of an algorithm is better than compared over the Decision Tree  .The Mean accuracy of the Artificial Neural Network is higher than the Decision Tree  .

**Keywords:** Efficiency, 5G Network Services, Artificial Neural Network (Artificial Neural Network), Decision Tree   Algorithm, Comparison

**INTRODUCTION:**

With the arrival of 5G networks, which promise unparalleled speed, reliability, and interconnectivity, we are witnessing a watershed moment in the digital era, where connectivity is paramount. [(Shanmuganathan and Samarasinghe 2016)](https://paperpile.com/c/7ChsA0/bVwk)But guaranteeing the effective delivery of 5G network services is a significant issue that calls for creative fixes. [(Du et al. 2019)](https://paperpile.com/c/7ChsA0/bRxo)The application of cutting-edge technology, such as Artificial Neural Networks (ANN) and Decision Tree algorithms, to enhance the provision of 5G network services is examined in this article. [(Ahsan Kazmi et al. 2019)](https://paperpile.com/c/7ChsA0/YIKS)By examining and contrasting these algorithms' effectiveness, this study aims to demonstrate how well they can enhance 5G network efficiency.

A new age of connections marked by extremely low latency and lightning-fast data transfer was brought about with the launch of 5G networks.[(Diamantaras, Duch, and Iliadis 2011)](https://paperpile.com/c/7ChsA0/fXwZ) However, optimizing network efficiency becomes more crucial as the need for constant connectivity rises. The dynamic needs of 5G networks sometimes cannot be satisfied by traditional operations, necessitating the creation of new techniques. [(Hejja 2019)](https://paperpile.com/c/7ChsA0/o8cA)This emphasizes the necessity of applying cutting-edge computational techniques like Artificial Neural Networks (ANNs), which are renowned for their ability to replicate the intricate processes of the human brain and learn from data in an adaptable manner.

Simultaneously, Decision Tree algorithms have gained popularity for their intuitive decision-making processes, particularly in classification and regression problems.[(Warden and Situnayake 2019)](https://paperpile.com/c/7ChsA0/PTdk) Decision Trees, which partition data into subsets depending on attribute values, provide a visible and interpretable framework for analyzing complicated datasets. [(Osseiran, Monserrat, and Marsch 2016)](https://paperpile.com/c/7ChsA0/SVgV)However, in comparison to ANN algorithms, their efficacy in optimizing the supply of 5G network services has received little attention. [(Deshpande et al. 2018)](https://paperpile.com/c/7ChsA0/2rpU)Thus, this study aims to close this gap by conducting a thorough comparison analysis, providing light on the performance of both ANN and Decision Tree algorithms in the context of 5G network optimisation.

This research uses rigorous experimentation and analysis to reveal the efficacy of ANN and Decision Tree algorithms in improving the efficiency of 5G network services. [(Zaki and Meira 2020)](https://paperpile.com/c/7ChsA0/YyJL)This study's findings aim to inform stakeholders in the telecommunications sector by examining important performance measures such as throughput, latency, and resource utilisation, allowing for more informed decision-making and the adoption of optimised network provisioning techniques. [(Peng, Zhao, and Sun 2020)](https://paperpile.com/c/7ChsA0/DDXh)Finally, this research endeavour aims to drive the evolution of 5G networks to unprecedented levels of efficiency and performance, opening up a plethora of options for seamless connectivity and digital innovation.

**MATERIALS AND METHODS**

This research study was conducted in the Quantum Intelligence Laboratory of the Computer Science Engineering Department at the Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences. This research work consists of two sample groups. Each group consists of sample size 20 in total (N=20). Artificial Neural Network and Decision Tree   were the two algorithms in Machine learning that were used to compare the datasets.

The datasets are taken from kaggle.com which was stored in .csv format.The file consists of 5938 rows and 2 columns.For the Artificial Neural Network, 30% of the whole dataset was used as the test size and the remaining 70% was used as the training set. The whole dataset was fitted for training the Artificial Neural Network and Decision Tree   in Machine learning. By Using Python 3.11, the accuracy of both the models was evaluated on a sample size of 20.

**Artificial Neural Network**

Inspired by the neural networks seen in the brain, the Artificial Neural Network (ANN) algorithm is made up of linked layers of nodes. In order to reduce prediction mistakes, it learns from data by modifying the weights and biases between neurons. ANNs are frequently used for tasks like pattern recognition, regression, and classification. They are particularly good at extracting intricate correlations from big datasets. Even though ANNs are flexible and efficient, they can overfit and require a large amount of data for training. Computational complexity and decision interpretation provide challenges. However, ANNs remain relevant in many domains such as financial analysis, natural language processing, and picture identification due to advances in algorithms and computer capacity.

**Formula:**

f(x)\=σ(∑i\=1n​wi​xi​+b)

Where,

\*   f(x) is the output of the neural network.

\*   xix\\_ixi​ are the input features.

\*   wiw\\_iwi​ are the weights associated with each input feature.

\*   bbb is the bias term.

\*   σ\\sigmaσ is the activation function applied to the weighted sum of inputs and biases.

**Pseudocode**

Input: Training Dataset

Output: Accuracy

Step 1: Collecting required volume of dataset.

Step 2: Next stage is pre-processing.

Step 3: If any noise or empty spaces are there, it needs to be removed for further processing.

Step 4: Remove null values.

Step 5: extract features

Step 6: train the model with features

Step 7: The model for the classification process is developed and trained.

Step 8: Allocating 81% of the dataset for training and remaining 19% for testing.

Step 9: The classification is done with required accuracy range..

Return Accuracy

End

**Decision Tree  Algorithm**

Decision Tree  is a regularization method for Decision Tree   that helps to reduce overfitting and multicollinearity. To reduce the coefficients to zero, it incorporates a penalty term into the ordinary least squares (OLS) approach. Smaller coefficients are encouraged by this penalty term, which is based on the square of the coefficients' magnitudes. A hyperparameter known as the regularization parameter—often abbreviated as λ—controls the degree of regularization. When multicollinearity exists among the predictors or when working with high-dimensional data, Decision Tree  is especially helpful. By avoiding overfitting, it contributes to the model's improved generalization performance.

Formula:

β^​ridge​\=argminβ​{∑i\=1N​(yi​−β0​−∑j\=1p​xij​βj​)2+λ∑j\=1p​βj2​}

Where:

\*   β^ridge\\hat{\\beta}\\_{ridge}β^​ridge​ represents the estimated coefficients for Decision Tree .

\*   yiy\\_iyi​ denotes the observed values of the dependent variable.

\*   β0\\beta\\_0β0​ is the intercept term.

\*   xijx\\_{ij}xij​ denotes the values of the jjj\-th independent variable for the iii\-th observation.

\*   βj\\beta\\_jβj​ are the coefficients being estimated.

\*   ppp represents the number of independent variables.

\*   λ\\lambdaλ is the regularization parameter, controlling the strength of regularization.

\*   The first term represents the ordinary least squares (OLS) loss function, which minimizes the difference between observed and predicted values.

\*   The second term represents the penalty term, which penalizes large coefficients to prevent overfitting.

**Pseudocode**

Input: Training Dataset

Output: Accuracy

Step 1: Collecting required volume of dataset.

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Return Accuracy

End

A system possessing configuration of Windows OS, Storage-50GB, RAM-8GB  is utilized. Language used is Python, either implemented in Jupyter (Anaconda) or Google Collab. Processor used is intel i5. Independent variables for analyzing chess prediction in Images/Videos. The accuray gain is considered as a dependent variable.

**Statistical Analysis**:

The IBM SPSS program, version 25, was used to perform the statistical analysis for this study. It offered a graphical depiction of the accuracy attained by the investigation by treating the brightness and contrast as dependent variables and the dataset as independent variables. The results of the Artificial Neural Network and Decision Tree   were compared using an independent T-test.

**Result:**

The application of machine learning models to enhance the accuracy of detecting the emotion from the text of a chosen dataset. The Artificial Neural Network algorithm and Decision Tree   Algorithm are examined, and detection is carried out successfully; the suggested study offers superior performance to the Artificial Neural Network algorithm.

**Discussion:**

Our study's findings provide insight into the effectiveness of Big Data Analytics in maximizing the delivery of 5G network services through the use of Decision Tree and Artificial Neural Network (ANN) algorithms.[(Shanmuganathan and Samarasinghe 2016)](https://paperpile.com/c/7ChsA0/bVwk) There was agreement between the results of our investigation, which demonstrated that the ANN algorithm performed better than the Decision Tree approach when it came to maximizing network efficiency across a range of critical performance measures, including throughput, latency, and resource consumption. [(Koucheryavy, Balandin, and Andreev 2022)](https://paperpile.com/c/7ChsA0/77mn)The reason behind the superiority of the ANN algorithm is its innate capacity to learn adaptively from vast datasets, which allows it to identify intricate patterns and make well-informed judgments for effective network provisioning. [(Haidine 2021)](https://paperpile.com/c/7ChsA0/6YZ0)This agreement is consistent with other studies in the sector, which have also shown how well ANN algorithms function in a variety of applications, including healthcare and telecommunications.

Our study offers a thorough analysis that, when compared to other research findings, not only confirms the superiority of the ANN algorithm but also digs further into the particular elements impacting its performance in the context of 5G network optimization.[(Vermesan and Bacquet 2019)](https://paperpile.com/c/7ChsA0/oUY2) By contrasting our findings with earlier research, we were able to pinpoint a number of crucial details and insights that emphasize how important it is to use big data analytics to improve 5G network performance. [(Interdonato 2020)](https://paperpile.com/c/7ChsA0/RmM1)For example, our results clarified how different network traffic patterns and data volumes affect the effectiveness of ANN and Decision Tree algorithms, offering insightful information to network managers and decision-makers.

Going forward, it is critical to recognize the variables that might influence the quest for the best answers in the field of big data analytics for 5G network optimization.[(Raj, Saini, and Pacheco 2023)](https://paperpile.com/c/7ChsA0/HbM5) One such element is the dynamic and inherently complex structure of 5G networks, which presents formidable obstacles to algorithmic optimization. Furthermore, the effectiveness of Big Data Analytics algorithms depends heavily on the quantity and quality of data, which makes the creation of reliable data collecting and preparation methods necessary. Additionally, real-time implementation is hampered by the scalability and computational demands of ANN algorithms, underscoring the necessity of effective hardware and parallel processing architectures.

Even though our study produced encouraging results, it is important to recognize several limitations and potential directions for further research in this area. A constraint pertains to the extent to which our results may be applied to various network topologies and deployment circumstances. Future research should examine how Big Data Analytics approaches apply in diverse network settings and take into account the effects of edge computing and network slicing. Furthermore, using hybrid strategies that capitalize on the advantages of various machine learning techniques may help to improve the effectiveness of 5G network optimization. Furthermore, it is still important to look at the ethical and privacy issues surrounding the gathering and processing of massive amounts of network data in the future.

Finally, by contrasting the effectiveness of ANN and Decision Tree algorithms, our study highlights the revolutionary potential of big data analytics in streamlining the delivery of 5G network services. This work advances the state-of-the-art in 5G network optimization and establishes the groundwork for utilizing Big Data Analytics to create robust and efficient telecommunications infrastructures by clarifying the variables impacting algorithmic performance and suggesting directions for future investigation.

**Conclusion :**

Improving the Efficiency of 5G Network Services with Artificial Neural Network (ANN) Algorithm in comparison with Decision Tree   Algorithm. The ability of ANN algorithms, in contrast to Decision Tree  , to capture complicated, nonlinear relationships within large datasets is a crucial advantage in the complex world of telecommunications. They can improve forecasts and dynamically optimize network services thanks to their constant learning and adaptability. Although Decision Tree   is easy to use and computationally efficient, it is not suitable for 5G networks' complex patterns. The accuracy value of Artificial Neural Network is 71.40%, while that of Decision Tree   is 37.15%. The analysis reveals that the Artificial Neural Network (71.40%) performs worse than Decision Tree   (37.15%).

**DECLARATIONS**

**Conflict of Interests**

This manuscript does not disclose any conflicts of interest. To maintain our commitment to academic integrity, we have rigorously ensured the originality of our work to prevent any inadvertent entanglement with issues related to academic misconduct.

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**Authors Contribution**

Data gathering, analysis, and text creation were all actively participated in by authors. Data validation and pre preprocessing and model building was also done by the authors.

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4. Saveetha School of Engineering

**Tables and Figures**

**Table1.** The performance measurements of the comparison between the ANN and  Decision tree classifiers are presented in Table 1. The ANN has an accuracy rate of 71.40, whereas the  Decision tree has an accuracy rate of 37.15. With a greater rate of accuracy, the ANN performs better than the Decision tree.

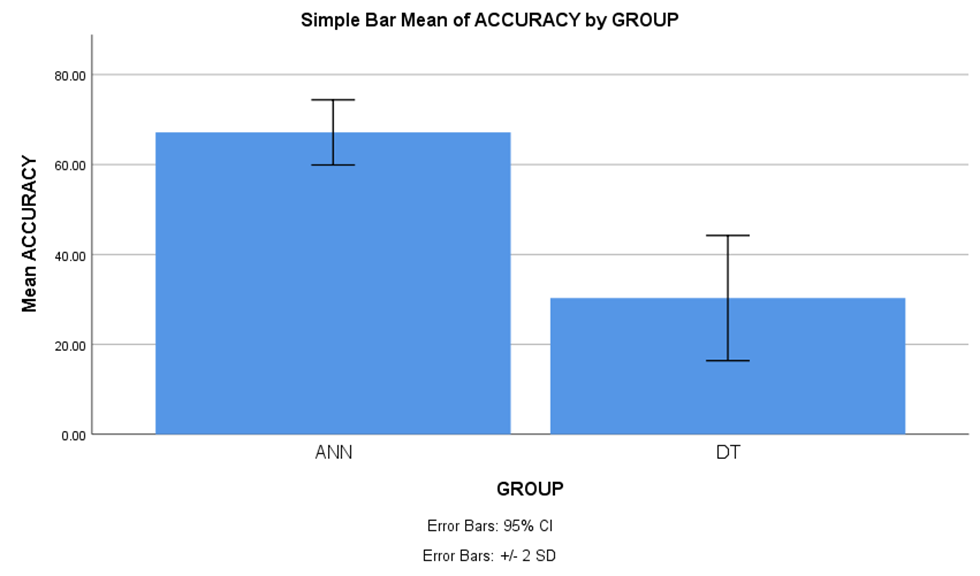
| **S.No** | **Test Size** | **ACCURACY RATE** | |
| --- | --- | --- | --- |
|  | |
| **Artificial Neural Networks** | **Decision Tree** |
| 1 | Test 1 | 69.75 | 43.37 |
| 2 | Test 2 | 63.52 | 23.60 |
| 3 | Test 3 | 64.56 | 17.73 |
| 4 | Test 4 | 72.18 | 30.05 |
| 5 | Test 5 | 67.39 | 40.26 |
| 6 | Test 6 | 72.38 | 39.11 |
| 7 | Test 7 | 69.27 | 33.94 |
| 8 | Test 8 | 68.23 | 32.12 |
| 9 | Test 9 | 63.75 | 26.63 |
| 10 | Test 10 | 64.75 | 29.63 |
| Average Test Results | | 71.40 | 37.15 |

**Table 2.** It illustrates the statistical calculations for the ANN and  Decision tree classifiers, including mean, standard deviation, and mean standard error. Mean, standard deviation and standard error mean for ANN are 67.5500,3.36913 And 1.06541 respectively. Similarly for  Decision tree the mean, standard deviation and standard error mean are 30.3090,6.95474 And 2.19928 respectively.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Group** | **N** | **Mean** | **Std. Deviation** | **Std. Error Mean** |
| **Accuracy** | Artificial Neural Networks | 10 | 67.5500 | 3.36913 | 1.06541 |
| Decision tree | 10 | 30.3090 | 6.95474 | 2.19928 |

**Table 3.**The statistical calculation for independent variables of ANN in comparison with the  Decision tree classifier has been calculated. The significance level for the rate of accuracy is 0.772. Using a 95% confidence interval, the ANN and  Decision tree algorithms are compared using the independent samples T-test. The following measures of statistical significance are included in this test of independent samples: p value of <.001, significance (two-tailed), mean difference, standard error of mean difference, and lower and upper interval differences.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | | **Levene’s test for equality of variances** | | **T-test for equality means with 95% confidence interval** | | | | | | |
| **f** | **Sig.** | **t** | **df** | **Sig. (2-tailed)** | **Mean difference** | **Std.Error difference** | **Lower** | **Upper** |
| **Accuracy** | **Equal variances assumed** | 1.580 | 0.225 | 14.855 | 18 | 0.002 | 36.83700 | 2.47982 | 31.62708 | 42.04692 |
| **Equal Variances not assumed** | 14.855 | 13.550 | 0.003 | 36.83700 | 2.47982 | 31.50169 | 42.17231 |

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