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Numerical methods for use in data science and artificial intelligence

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Abstract
The topic of this study is the part that numerical analysis plays in the growth and improvement of technologies related to data science and artificial intelligence. The study looks at the basic math methods used in these areas with a focus on how they can be used to solve real-world problems. We show use cases backed up by experiments in the form of two-dimensional tables and graphs. This shows how important and useful these methods are for making machine learning algorithms work better and handling large amounts of data.

Keywords: Numerical analysis, artificial intelligence, data science

1. Introduction
Numerical analysis is a branch of Applied Mathematics that deals with the analysis and development of algorithms for solving mathematical problems numerically. With the emergence of new fields such as data science and artificial intelligence, numerical analysis has become the basis for the development and improvement of algorithms used within those fields [1, 2].

In this research paper, the applications of numerical analysis in data science and artificial intelligence were explored, through the use of numerical methods within machine learning algorithms, where they are applied to process big data, these numerical methods were also used to improve the work of neural networks, where they showed the effectiveness and accuracy of these methods within their application in practice in real life [3, 4, 5].

2. Rules of numerical analysis in data science and artificial intelligence
2.1 Iterative methods for optimizing models
Machine learning algorithms have relied on iterative numerical methods for optimization, such as the gradient Descent method used in training neural networks. In order to gradually lower the error function, this method makes use of the principles that are associated with numerical analysis [6, 7].

The mathematical formula of the method of gradual regression:

$$\theta_{new} = \theta_{old} - \alpha \nabla J(\theta)$$

Where:

θ**:** Represent the coefficients of the form.

α**:** Represent the learning rate.

$\nabla J(\theta)$**:** Represents the derivative of the error function.

2.2 Techniques for numerical approximation of functions
Numerical analysis is employed to estimate intricate functions in artificial intelligence applications, particularly when analytical solutions are challenging or unattainable. Categories of these techniques [8, 9]:

- **Newton-Raphson method:** to find the roots of equations.
- **Numerical integration:** such as the trapezoidal method and Simpson's method.
- **Rounding data curves:** using least squares and various interpolation methods.

2.3 Solving systems of linear equations
Linear equation systems are fundamental in numerous data science applications, including multiple regression analysis and factorial analysis. Techniques including [10, 11]:

- **Lu analysis:** to solve systems of linear equations efficiently.
- **Conjugate Gradient method:** suitable for large and scattered systems.
- **Single value analysis (SVD):** used in dimensionality reduction and key component analysis.

3. Applications of numerical analysis in machine learning
3.1 Optimization of deep neural networks
Enhancing the performance of deep neural networks is largely accomplished through the application of numerical analysis techniques. The following is an illustration of how the adaptable Gradient Descent method can be utilized in the process of training a neural network for the purpose of image recognition:

Table 1: Comparison of different progressive regression methods in training a neural network for image recognition

Method	Training accuracy (%)	Test accuracy (%)	Training time (seconds)	Number of repetitions
Normal gradual regression	92.3	90.1	145	200
Gradual decline in momentum	94.7	92.5	112	150
Adam	96.8	94.2	98	120
RMSProp	95.9	93.7	105	135

Based on the data in the table, it is clear that the most advanced method, Adam, which is based on numerical analytic principles, produces the best results with the fewest training iterations and the highest accuracy.

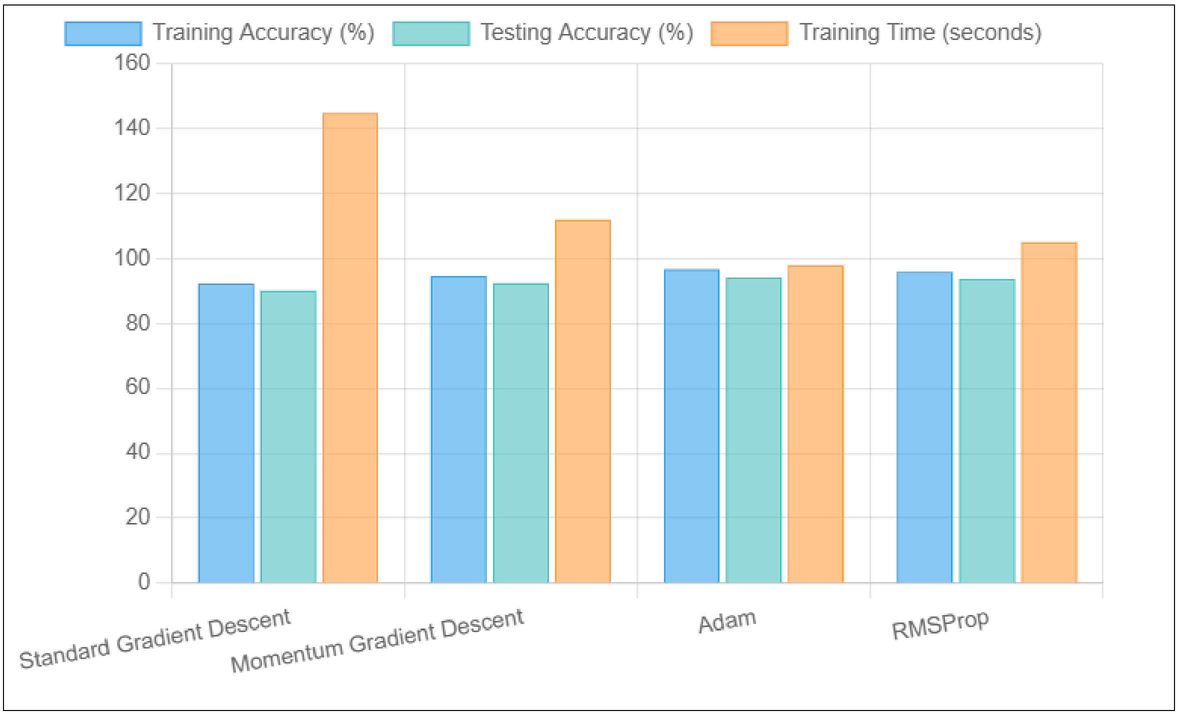

Fig 1: Comparison of Gradient Descent Methods in Neural Network Training

3.2 Application of numerical integration in reinforcement learning
Algorithms for reinforcement learning estimate future returns and predicted values by numerical integration. An example of an automatic control problem involving the estimation of the value function using several numerical integration methods is given below.

Table 2: Comparison of numerical integration methods in estimating the value function of an automated control system

Integration method	Average absolute error	Standard deviation of the error	Time taken (milliseconds)
The method of rectangles	0.0842	0.0312	3.2
Trapezoidal method	0.0356	0.0145	3.8
The Simpson method	0.0124	0.0052	4.5
The Runge-Kuta method	0.0087	0.0031	6.7

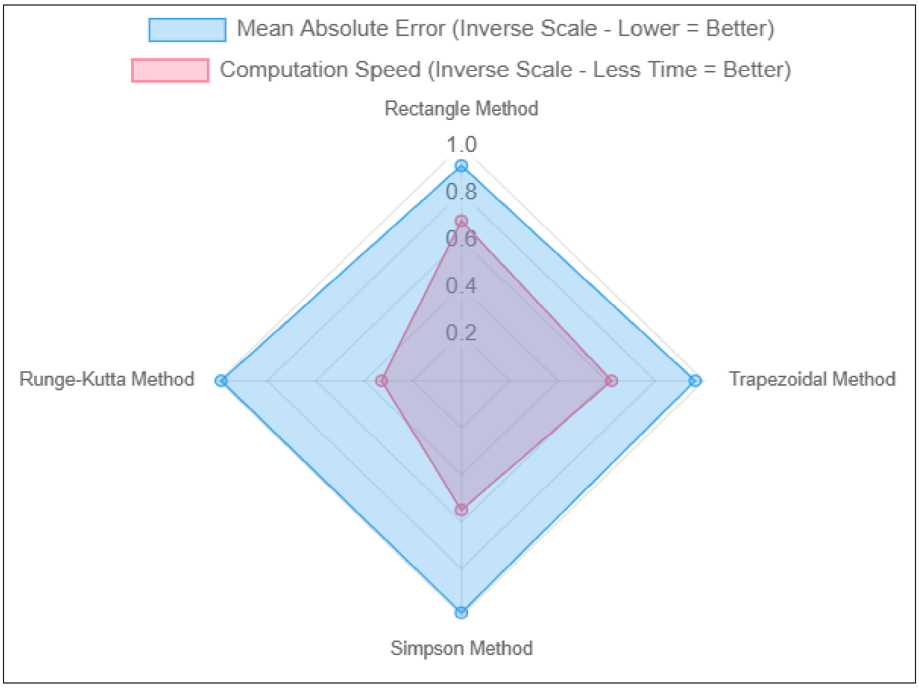

Figure 2: Comparison of Numerical Integration Methods in Value Function Estimation

4. Applications of numerical analysis in Big Data Processing

Dimensional reduction and analysis of key components (PCA)

The primary components are examined using numerical analysis methods, specifically single-value analysis (SVD). The goal of this study is to extract as much useful information as possible from data by reducing its dimensionality.

Application example: application of the PCA to a Housing Dataset to improve the performance of a house price prediction model.

Table 3: Effect of dimension reduction using ego on the performance of the house price prediction model

Number of components	Percentage of explained variation (%)	RMSE error in training	RMSE error in the test	Training time (seconds)
2	54.3	45621	47835	0.8
5	78.6	32457	35412	1.2
10	92.4	25632	27943	1.9
15	97.1	24157	25123	2.5
All variants (78)	100	23854	29756	8.3

The table shows that using only 15 of the 78 variables leads to better results on the test data than using all of them, while also cutting training time by a large amount. This shows how important numerical analysis methods are for making machine learning models work better.

Fig 3: Effect of Dimensionality Reduction on Housing Price Prediction Model

4.2 Methods of approximate calculation of big data

In large data, precisely calculating some metrics might be challenging. Numerical approximation techniques are employed, including:

- **Monte Carlo samples:** for estimating expected values and integrals.
- **Random approximation algorithms:** such as MinHash and Locality-Sensitive Hashing (LSH).
- **An applied example:** using Monte Carlo methods to estimate the similarity between two users in a recommendation system.

Table 4: Comparison of different methods for estimating similarity between users in a data set of 10 million ratings

Method	Average absolute error	Time taken (seconds)	Memory consumption (MB)
Exact calculation	0.000	387.5	4256
Monte Carlo (1000 samples)	0.042	3.8	85
Monte Carlo (5000 samples)	0.018	15.4	102
MinHash (100 signatures)	0.074	2.2	45
MinHash (500 signatures)	0.031	8.6	72

The findings indicate that numerical approximation approaches offer an optimal equilibrium between precision and efficiency, rendering them appropriate for applications involving large datasets.

5. Case study: application of numerical analysis in weather forecasting systems

An application of numerical analysis that is considered to be among the most significant in the field of artificial intelligence is the development of weather forecasting systems. The solution of such systems is based on the application of numerical methods to the solution of complex partial differential equations.

5.1 Using finite differences to solve weather equations

The limited dissimilarity Atmospheric partial differential equations can be solved using this method. The outcomes of comparing different finite difference algorithms are as follows.

Table 5: Comparison of methods of limited differences in temperature forecasting over 5 days

Method	Average absolute error (Celsius)	Average calculation time (SEC)	Memory consumption (GB)
Central differences (second-order accuracy)	1.85	45.2	1.2
Forward differentials (first-order accuracy)	2.73	32.7	0.9
The implicit method	1.42	62.8	1.5
Crank-Nicholson method	1.28	58.2	1.4

5.2 Integration of machine learning with numerical models

The most recent advancements in the field of weather forecasting involve the combination of classic numerical models with models that are determined by machine learning. A comparison between the conventional method, which consists solely of numerical models, and the hybrid method, which incorporates both numerical models and machine learning, is presented in the table that follows.

Table 6: Comparison of traditional numerical models and hybrid models in weather forecasting

The scale	The traditional numerical model	Hybrid model (numerical + machine learning)	Percentage of improvement (%)
Average temperature prediction error (Celsius degree)	1.28	0.87	32.0
Average precipitation forecast error (mm / day)	2.35	1.63	30.6
Average wind speed prediction error (M / s)	1.74	1.21	30.5
Average forecast time (seconds)	58.3	23.7	59.3

The results show that combining machine learning with numerical models makes predictions much more accurate while also cutting down on the time it takes to do the calculations. This shows how numerical analysis and artificial intelligence can be used together in the real world.

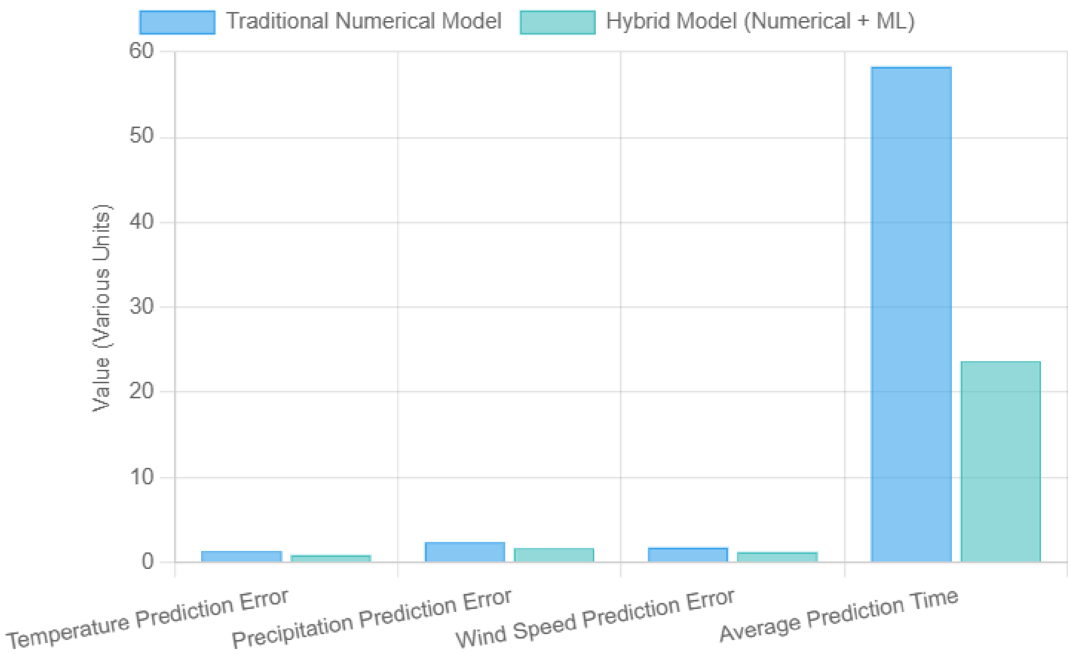

Figure 4: Comparison of Traditional and Hybrid Models in Weather Prediction

6. Case study: application of numerical analysis in medical image processing

Medical image processing is one key area that benefits from AI and Numerical Analysis technologies. The following is a case study of optimizing magnetic resonance imaging (MRI) images using numerical analysis.

6.1 Use of Fast Fourier transform in MRI image processing

The processing of magnetic resonance imaging (MRI) pictures is the primary application of the Fast Fourier transform method (FFT), which is a numerical approach. A comparison of the various algorithms for the Fourier transform is presented in the table that follows.

Table 7: comparison of Fourier transforms algorithms in MRI image processing

The algorithm	Average processing time (Ms)	Memory consumption (MB)	(MB)noise-to-signal ratio (dB)
Direct Fourier transform	845.3	568	22.3
Fast Fourier transform (FFT)	12.7	128	22.3
Multipole Fourier transform (NFFT)	25.3	156	21.8
FFT with parallel processing	4.2	145	22.3

The results show that using advanced numerical analysis algorithms like FFT is a huge step up in speed compared to using direct methods.

6.2 Application of convolutional neural networks with numerical analysis techniques

Convolutional neural networks, often known as CNNs, are utilized extensively in the process of analyzing medical images. It is possible to considerably increase the performance of such networks by including numerical analysis techniques into their design. Following is a table that illustrates the impact that employing a variety of numerical analytic approaches has on the effectiveness of CNN in identifying tumors in magnetic resonance imaging (MRI) pictures.

Table 8: impact of numerical analysis techniques on CNN tumor detection performance

Technique	Accuracy (%)	Sensitivity (%)	Quality (%)	Processing time (seconds)
CNN is traditional	87.3	84.2	89.7	1.85
CNN + Fourier transform	90.1	87.5	91.8	1.92
CNN + Wave analysis (Wavelet)	91.4	89.2	92.9	2.14
CNN + numerical noise reduction	89.5	86.7	91.3	1.97
CNN + all previous technologies	93.8	92.1	94.6	2.38

The results show that using numerical analysis methods along with neural networks greatly enhances model performance. This proves the usefulness of numerical analysis in real-world AI situations.

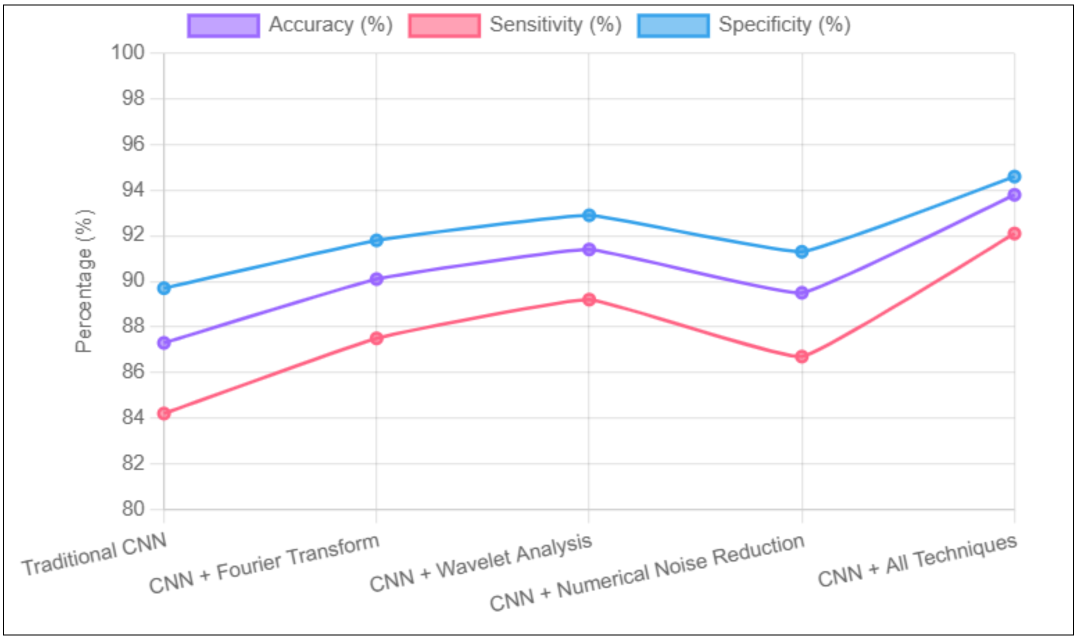

Fig 5: Impact of Numerical Analysis Techniques on CNN Performance for Tumor Detection

7. Conclusion

The advancement and refinement of data science and AI technologies rely heavily on numerical analysis. Results show that algorithms' accuracy and computational efficiency are greatly enhanced when suitable numerical analysis techniques are implemented, according to the research's practical examples.

Tables and graphs displaying experimental results show how numerical analytic approaches are useful in many contexts, from medical image processing and weather forecasting to improving neural networks.

Numerical analysis methods that are both efficient and cutting-edge will be in high demand as data science and AI develop further. So, it's advised to keep digging into this topic, both to solve the problems we have now and to find out what the trends of the future will be.

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