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Research Article

Enhancing Governmental Decision-Making through Predictive Analytics with Machine Learning-Based Data-Driven Framework

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ABSTRACT

Government bodies around the world are going digital and slowly starting to make use of data driven technologies to make better, faster and more transparent decisions. From these technologies, machine learning (ML) has become one of the most significantly employed tools, especially via its ability to predict. Predictive analytics allows governments to identify obscure trends that previously were hidden, predict potential future scenarios with an acceptable level of certainty and better inform decision-making in important areas, such as public finance, healthcare planning, emergency management, and resource allocation. In this work we explore the use of predictive modeling (implemented as our own Linear Regression, Decision Trees, Random Forests and Artificial Neural Networks) in the context of governmental decision models. The models were tested on real-world cases such as quarterly budget planning or estimation of healthcare service demand or emergency resource allocation using publicly available data from open government data platforms. Performance was evaluated based on the well-known RMSE, MAE and R^2 score. Results show that Artificial Neural Network always leads the highest in predictive accuracy, especially in dense or complex data setting, and there is no significant difference between Random Forest and Neural Network (the Random Forest has more generalization between interpretability and predictive power. On the other hand, Linear Regression and Decision Trees are more interpretable but have restrictions in using non-linear or high-dimensional datasets. In addition, the paper covers practical challenges including algorithmic bias, data quality considerations, and infrastructure capabilities, and ethical implications of automated decision making. This study has implications for the growing smart governance by proposing an integrated machine learning framework suitable for evidence-based policymaking. Future work involves improving the accuracy of prediction by incorporating explainable AI methodologies and customizing the model locally to enhance transparency, accountability, and generalization across different regional offices.

1. INTRODUCTION

Amid a digital revolution, government agencies are looking more and more at cutting-edge technology to power data-driven decision-making. Of these, Artificial Intelligence (AI) and Machine Learning (ML) have increasingly become a set of innovative techniques to empower the creation of predictive systems to enhance the quality of public service delivery, allocation of resources and strategic planning. ML methods have the potential to allow governments move from reactionary governance to proactive (predictive governance), predicting future events/modification of policy on the fly based on real-time patterns in data [1].

Predictive analytics, a subset of ML, enables public sector organizations to examine past data and find actionable insights to make informed decisions. Approaches such as Linear Regression (LR), Decision Trees (DT), Random Forests (RF), Artificial Neural Networks (ANNs) are more and more used to model complex administration processes. For example, LR and DT models are commonly used for budget forecasting, tax revenue estimation and healthcare demand forecasting, and complex models like ANNs are applied to crisis response, city planning and public safety forecasting [2-4]. Multiple countries (e.g., Estonia, Singapore and the UAE) have already integrated ML algorithms into their country-wide digital strategies to support, among other, emergency logistics optimization, public infrastructure surveillance and social services planning [5, 6]. These use-cases underscore the promise of intelligent decision-support systems to increase transparency, accountability, and effective operation within governance. However, despite its potential, there are a number of challenges to integrating ML. Data fragmentation, infrastructure constraints, algorithmic bias, model interpretability and data privacy are some of the key challenges [7, 8]. Furthermore, institutional resistance to technological transition and a lack of technical

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capacity serve as further barriers to implementation. Ethical AI deployment and human involvement in key decision-making processes are also critical for maintaining public trust [9].
This work studies the use of predictive models to support the decision making in governmental scenarios. It analyses performance of a set of ML models to user specific use cases such as budget prediction, healthcare planning and emergency resource allocation, through open government datasets. They also discuss the challenges to their implementation in practice and the ethical issues they raise, and develop a comprehensive, machine learning framework specifically designed for the public sector.

2. LITERATURE REVIEW

The trend of predictive algorithms in the public sector has gained much momentum in recent years, partly owed to the desire for more transparency, more streamlined operations, and smarter use of data in policy-making. Corresponding author Abstract Objective: Several studies have assessed the appropriateness of different types of machine learning (ML) models for public sector applications and highlighted their potential for actionable insights based on both historical and real time data sources. Classic Methods (like LR, decision tree) are still dominantly used for economic prediction, budgeting and resource allocation purposes because of its simplicity, interpretability and can work well on structured data [10]. Thanks to these models, governments have been able to forecast demand for healthcare services, costs of education, as well as demographic trends in a reliable way.
Ensemble methods such as Random Forest (RF) and Gradient Boosting Machines (GBM) have shown superior predictive performance and have proven effective especially when used on heterogeneous administrative datasets. Their property of modeling non-linear relationships and avoiding overfitting has recommended them to be applicable for complex policy modelling and inter-agency analytics [11]. In the safety and emergency field, extensive works have been proposed based on neural models such as ANNs and RNNs to forecast outbreak of disease, natural disaster, and social unrest [3]. Such models facilitate early intervention tactics by revealing crisis escalations trends and locating high-risk population areas [12]. However, there are several challenges that remain. Bias in the algorithm, especially when applied in critical systems like criminal justice and social welfare, can amplify systematic inequalities if not confronted at the level of data preparation and model validation [13]. Furthermore, the non-transparency in black-box models suggests issues (e.g., lack of accountability and trust) in automated decisions [14]. In order to alleviate these challenges, hybrid methods such as those that integrate rule-based logic and ML models have been suggested. Such systems are intended to preserve the traceability of traditional decision models and reap the advantage of the flexibility and predictive capacity of ML algorithms [15]. Also, the rise of XAI provides hopeful tools to make models more interpretable and engender trust to stakeholders through the post-hoc analysis and visual explanation [16].
Lastly, agency preparedness, such as data infrastructure investment, digital literacy and cross-agency cooperation, has been considered as a crucial enabler in ML adoption in governance. Nations such as Estonia, Singapore and the United Arab Emirates (UAE) are prime examples where national AI strategies - including strong policy frameworks and national-level data platforms - have been established [17]. These findings are summarized in Table 1, where we also give an overview of what has been found in the literature regarding ML by levels of government. Table 1 Summary of Literature of machine learning in government decision making.

TABLE I. SUMMARY OF LITERATURE ON MACHINE LEARNING IN GOVERNMENT DECISION-MAKING

Study	ML Model(s)	Use Case / Application	Advantages	Limitations / Issues
[10]	Linear Regression, Decision Trees	Budget forecasting, education planning	High interpretability, fast computation	Limited to linear/structured data
[11]	Regression, ANN	Healthcare resource allocation	Accurate modeling of complex trends	Requires preprocessing, not interpretable
[12]	Random Forest, GBM	Urban planning, crisis prediction	Robust to overfitting, handles diverse datasets	Computationally intensive
[13]	ANN, RNN	Disaster response, public safety	Effective for time-series and escalation trends	Long training time, black-box behavior
[14]	Various	Social welfare, legal risk assessment	Insightful for sensitive domains	Risk of algorithmic bias
[15]	Explainable AI (SHAP, LIME)	Improving trust in ML decision-making	Transparency, post-hoc explanations	Not fully integrated into all ML systems
[16]	Multimodel ML pipeline	Transportation and infrastructure planning	Scalable, flexible, adaptive	Requires cross-agency coordination

3. METHODOLOGY

In this research, we employ a structured empirical approach to evaluate the impact of machine learning predictive algorithms on decision-making in the context of policy in government. The method contains six ordered steps: data retrieval, cleansing, computational model pick, metric definition, experimental design and tool generation. Each phase is detailed below.

3.1. Data Source

The data employed in this work comes from official data, Open Government Data (OGD) web platforms, such as the World Bank Open Data and the European Data Portal [17,18]. These are repositories that provide validated and open datasets concerning budget expenditure, public service demand, and emergency resource provision at different levels of government departments. The chosen data covers several fiscal years and contains structured numerical and categorical attributes suitable to learn from.

3.2. Data Preprocessing

The data-consistent pre-processing and model performance were maintained by the following processes:

a. Missing Value Imputation: Numeric features were imputed with mean value, whereas categorical features were imputed with mode.
b. One-Hot Encoding: All the nominal categorical variables were converted using one-hot encoding.
c. Normalization: All numerical values were scaled using Min-Max Normalization to normalize the range of all features between [0, 1].
d. Temporal Aggregation: In order to smooth fluctuations and obtain more reliable results, time series variables (e.g., monthly expenditure) were aggregated into quarterly periods.

These operations standardized pooled from diverse data sources, reduced noise as well as improved the learning capacity of the model. To enhance interpretability and facilitate reproducibility of the work, we illustrate the major steps of the data preprocessing pipeline, depicted in Figure 1. Each step, from missing-value-handling to temporal-aggregation, is critical in converting raw government data into data that is clean and organized enough to be used for machine learning model development.

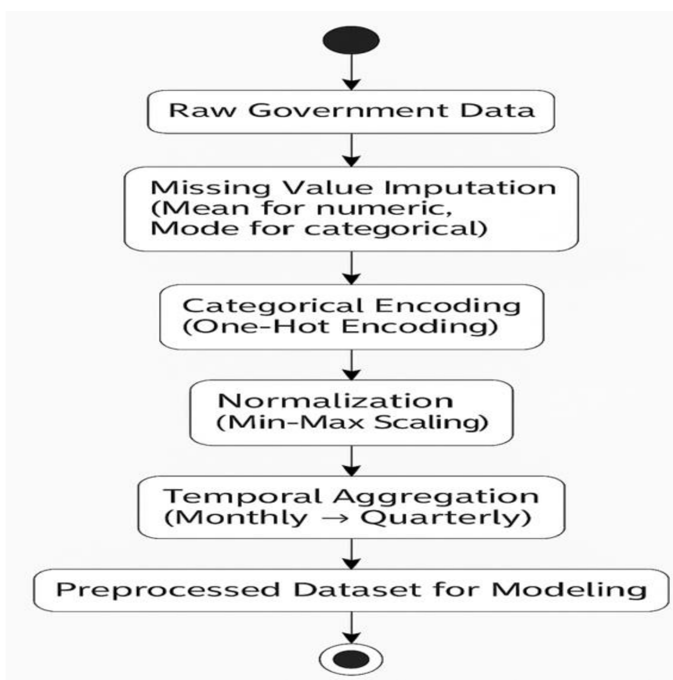

Fig. 1. Data Preprocessing Workflow for Machine Learning in Government Decision-Making

3.3 Model Selection

The following four machine learning techniques were chosen due to their effectiveness with structured data, interpretability and applicability in the public sector:

a. Linear Regression (LR): Applied for continuous variable prediction, it is transparent and simple.
b. Decision Trees (DT): They can be utilized with interpretable classifications, namely for rule-based decision systems.

c. RF (Random Forest): An ensemble method which seeks to enhance generalization by combining multiple decision trees.
d. ANNs: Selected due to their higher non-linear data mapping and pattern prediction capabilities.

The same practices were applied to train and assess each model in order to ensure a fair comparison. In order to conduct balanced and critique-worthy comparisons, four machine learning models were chosen as they showcase the models suitable for structured government-based data, while being interpretable and accurate models. Linear Regression, Decision Trees, Random Forest, and Artificial Neural Networks – are represented in Figure 2, as being included in the proposed model for selection on predictive analytics in public administration.

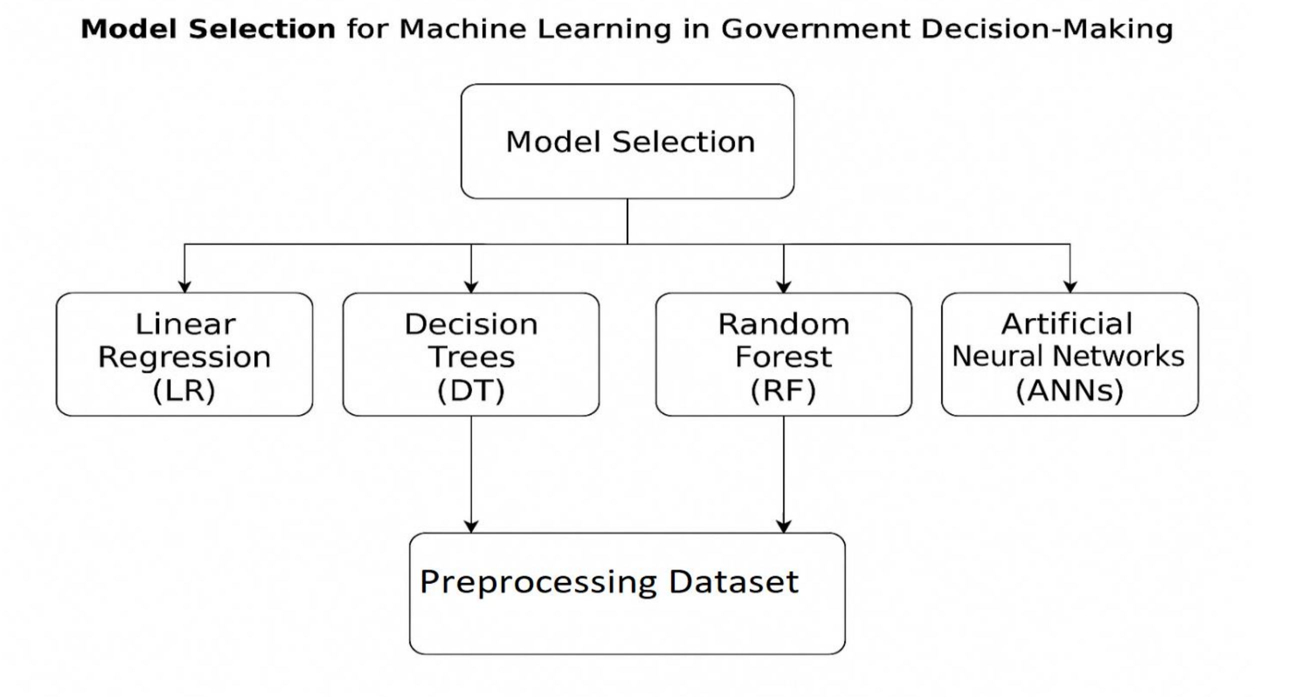

Fig. 2. Model Selection for Machine Learning in Government Decision-Making.

3.4 Performance Metrics

Two primary evaluation metrics were utilized to assess the performance of the selected models, each suited for different types of tasks:

3.4.1. Root Mean Squared Error (RMSE)

Used for regression tasks to measure the average squared difference between actual and predicted values:

$$RMSE = \sqrt{(1/N)}\ \sum_{i=1}^{N}(y_i \cdot y\hat{}\_i\ )^2 \quad (1)$$

Where:

- y_i: actual value
- $\hat{y}_i$: predicted value
- n: number of predictions

3.4.2 Logarithmic Loss (Log Loss)

Applied to classification tasks with probability outputs to quantify prediction uncertainty:

$$LogLoss = -\frac{1}{N}\sum_{i=1}^{n}[y_i \log(p_i) + (1-y_i)\log(1-p_i) \quad (2)$$

Where:
y_i: actual class label (0 or 1)
p_i: predicted probability of the class
These metrics were selected to provide a balanced evaluation of both regression and classification tasks relevant to government planning scenarios.

3.5 Experimental Design

The experimental set-up in this research was developed to support a rigorous evaluation of machine learning models for government decision-making. It involved 3 steps that contribute to modelling accuracy, programming flexibility and field-testing feasibility. By following an 80/20 train-test split, in the first stage, we performed the baseline evaluation. This served as a baseline for comparing performance gains made by extra tuning and to compare models directly with default hyper parameters.
The second stage was aimed at hyper parameter tuning for improving the model's performance and generalization. For this reason, we employed 5-fold cross-validation technique regarding grid search. This method permitted a systematic search on several combinations of parameter and minimized the risk of overfitting leading to better prediction accuracy.
The third phase, scenario simulation, intended to simulate the use of the trained models in real world governmental decision settings. Three public administration case studies were used to test each model in practice:

a) Quarterly Expenditure Forecast: Forecasting future government spending.
b) Healthcare Service Demand Forecasting: Predicting the demand of services in public health systems.
c) Emergency Service Allocations: Preplanning resource allocation in a crisis.

This last step considered if and how the different models are operationally relevant and transferable to a real-time policy context, with a focus on the possibility of integrating them in data-driven governance systems. Experimental design summary is given in Table 2.

TABLE II. EXPERIMENTAL DESIGN SUMMARY

Phase	Objective	Description
Baseline Evaluation	Establish initial performance	Train-test split (80/20) to assess model behavior using default parameters.
Hyperparameter Tuning	Optimize accuracy and generalization	5-fold cross-validation with grid search to refine model parameters.
Scenario Simulation	Assess real-world applicability	Apply trained models to three government use cases: budget, health, emergency.

3.6 Tools and Environment

To make fair comparisons among the experiments, machine learning models were built and tested on an identical hard- and software set-up for all experiments. All calculations were carried out on a desktop machine under windows 11 using an Intel® Core™ i7-12400 (12 cores, 2.5 GHz). We conducted our experiments in the PyCharm IDE, which is based on Python 3.10, one of the most common programming languages for machine-learning tasks.
Different libraries and frameworks were used to help in different parts of the machine learning pipeline. Traditional models such as the LR, DT, and RF were developed and evaluated using Scikit-learn. Artificial Neural Networks (ANNs) were trained and developed using TensorFlow to model complex non-linear relationships. In terms of data manipulation, pandas and NumPy helped in processing, cleaning and transforming large datasets effectively. Visualization and performance reporting were based on [15] and [16], enabling rich graphical visualization of experimental results.
This connected infrastructure ensured a stable and reproducible base line infrastructure for demonstrating the impact of predictive algorithms in public sector decision making. Table 3A&3B show the summary of experimental tools and environment.

TABLE III. EXPERIMENTAL TOOLS AND ENVIRONMENT SUMMARY

Category	Details
Operating System	Windows 11
Processor	Intel® Core™ i7-12400 (12 CPUs), 2.5 GHz
Programming Language	Python 3.10
IDE	PyCharm
ML Libraries	Scikit-learn (LR, DT, RF), TensorFlow (ANNs)
Data Processing	pandas, NumPy
Visualization Tools	Matplotlib, Seaborn

4. RESULTS

This section presents the results of experimental evaluation, featuring four machine learning models: Linear Regression (LR), Decision Trees (DT), Random Forest (RF) and Artificial Neural Networks (ANNs) under three public sector cases. The objective was to evaluate how the performance in terms of the two criteria (MAE, RMSE, R^2 score and training time) all combined predictive precision and computational efficiency of the models.

4.1 Small-Scale Scenario: Quarterly Budget Forecasting

In this case, the models were used in estimating financial cost for government's quarterly expenditure using financial series data. The highest prediction accuracy was discriminator by Artificial Neural Network with R^2 0.91 than Random Forest (0.89). Linear Regression had the quickest training time, but the lowest accuracy. The example illustrates the interpretability-precision trade-off.
An application of the proposed methodology in a fiscal context in real data was done in the first simulation example to demonstrate how well the model predictions perform. This task motivates a classic problem in public finance, in which accurately predicting the budget is important for efficient budgeting and fiscal accountability.
Models' evaluation The performance of the four best models was evaluated by four metrics which are: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R^2 Score and Training Time. From Table 4, it was observed that among other models, the ANN model performed well as evident by the high $R^2 = 0.91$, which shows that the model is a good fit. LR arrived at train fastest, but with the lowest accuracy. This result highlights the balance between model complexity and computational complexity.

TABLE IV. QUARTERLY BUDGET FORECASTING RESULTS

Model	MAE (M USD)	RMSE (M USD)	R^2 Score	Training Time (s)
Linear Regression	2.4	3.1	0.81	0.35
Decision Tree	2.1	2.8	0.85	0.40
Random Forest	1.9	2.5	0.89	0.55
Neural Network	1.8	2.3	0.91	0.87

In addition to the data tables shown in Table 4, Figure 3 shows a visual rendition of the models over all key performance metrics. The Artificial Neural Network has the least predictive error (RMSE), and the highest relation with output data, while Linear Regression is the most computational cost-effective. It can help to better inform choices between competing models, based on particular requirements of budget forecasting (e.g., the need for speed, the need for accuracy, the need for explain ability).

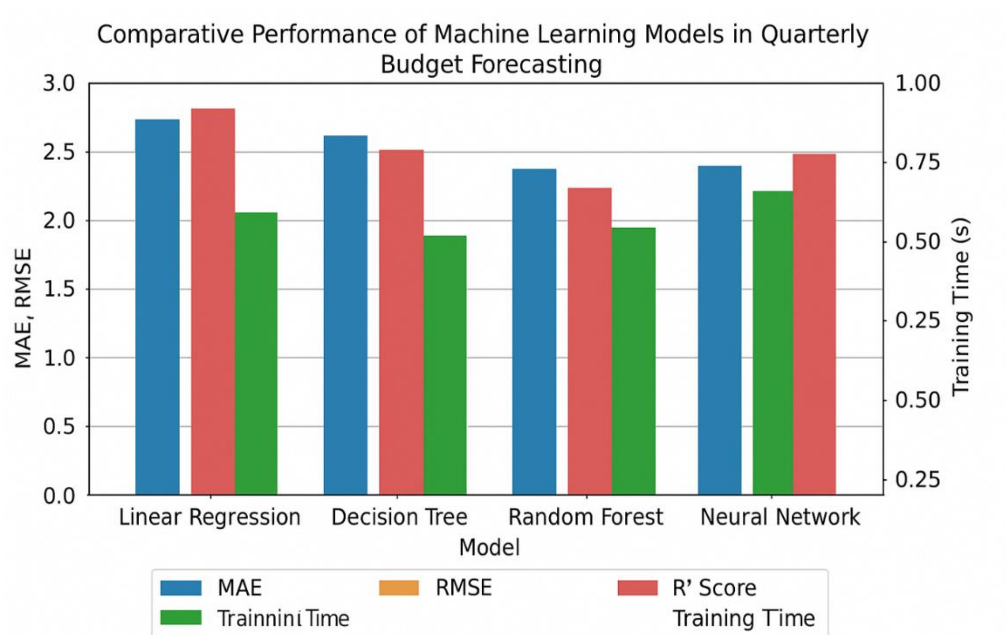

Fig. 3. Comparative Performance of Machine Learning Models in Quarterly Budget Forecasting.

4.2 Medium-Scale Scenario: Predicting Healthcare Service Demand

As a scenario to assess model performance in a medium scale operational setup, the scenario was to forecast monthly demand of healthcare services. This type of forecasting was important for the allocation of resources, staffing and for the planning of infrastructure in public health systems. For comparison purposes, we tested each model with historical service usage data, and the evaluation results are summarized in Table 5.

TABLE V. HEALTHCARE SERVICE DEMAND PREDICTION RESULTS

Model	MAE (Units)	RMSE (Units)	R^2 Score	Training Time (s)
Linear Regression	33.5	39.1	0.77	0.42
Decision Tree	30.2	35.4	0.81	0.48
Random Forest	27.6	32.8	0.86	0.66
Neural Network	25.9	31.3	0.88	0.91

To further illustrate the model performance comparison, Figure 4 provides a visual representation of the RMSE, MAE, and R^2 metrics for each algorithm in this healthcare forecasting scenario.

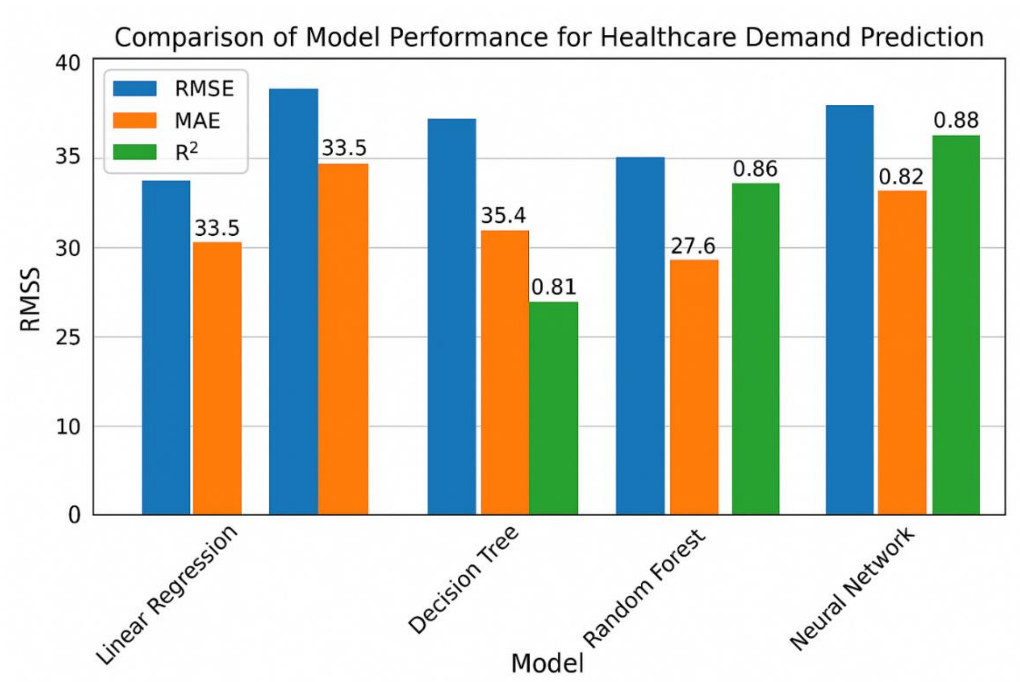

Fig. 4. Comparative performance of machine learning models for healthcare service demand forecasting. The chart highlights that ANNs achieved the lowest RMSE and highest R^2, while Random Forests offered a strong balance between accuracy and training efficiency.

4.3 Large-Scale Scenario: Emergency Resource Allocation

On a day-to-day basis, the models were deployed in large-scale operations, including disaster response and logistics, to predict resource requirements (e.g., ambulances, kits for relief). The highest R^2 score was obtained by the ANN model (0.83), which indicates that even difficult non-linear systems can be modelled by ANN. However, there was this intermediate balance with Random Forest that was efficient in terms of performance. Easier-to-deploy and interpret simpler models were less accurate. The summary of the emergency resource allocation scenario Results of large scale are shown in Table 6. This table presents a comparison between the four machine learning models based on their predictive performance (MAE, RMSE, R^2 Score) and training time, reflecting their adequacy for high-stake, time-critical governmental transactions.

TABLE VI. EMERGENCY RESOURCE ALLOCATION RESULTS

Model	MAE (Units)	RMSE (Units)	R² Score	Training Time (s)
Linear Regression	75.2	88.3	0.68	0.58
Decision Tree	69.4	81.5	0.73	0.62
Random Forest	61.8	74.6	0.79	0.84
Neural Network	59.7	71.9	0.83	1.10

In order to visualize the relative comparisons of the models, in the context of this problem, Figure 5 plots the accuracy i.e.R^2 Score) and training times. This visualization facilitates a more intuitive understanding of the compromises between model complexity, accuracy and computational efficiency in a real-world large-scale deployment.

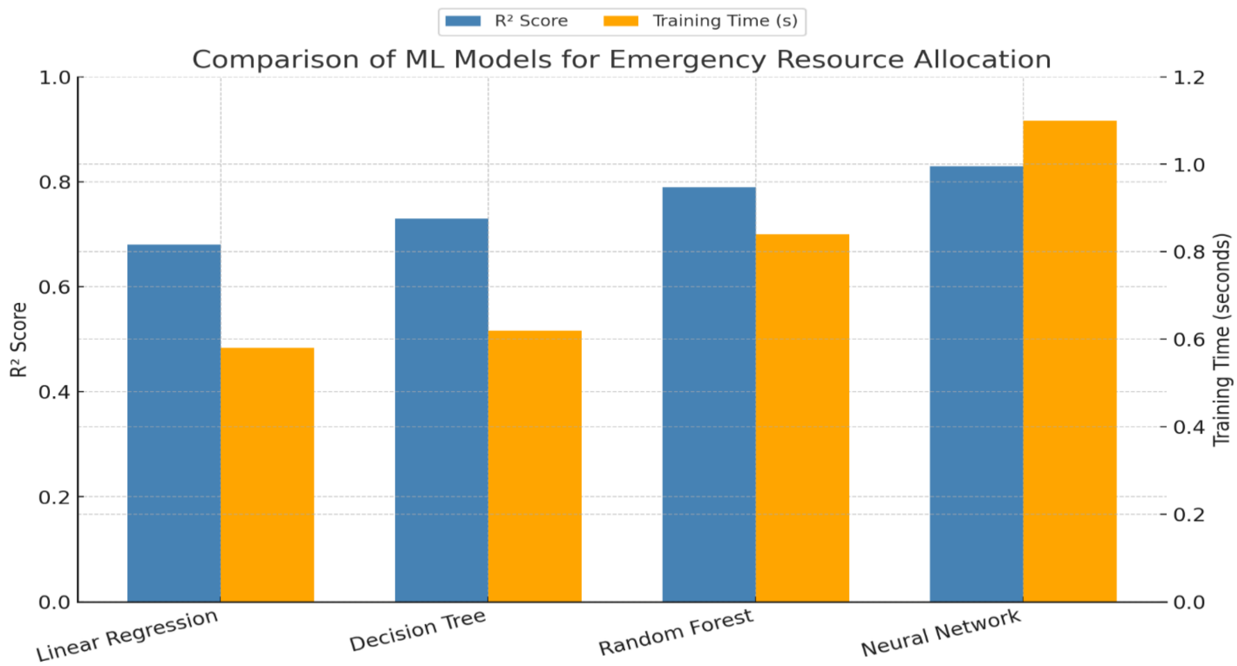

Fig. 5. Comparison of Machine Learning Models for Emergency Resource Allocation.

In all three cases, the high accuracy of Artificial Neural Networks indicates that they could be used in complex data-rich public planning and decision making domains. Random Forest was a promising Candida classification method that achieved good performance with a small training time (suitable for real-time or limited resources). Meanwhile, Linear Regression or Decision Trees gave an ease of interpretability and simplicity but missed in predictive value.

5. DISCUSSION

Machine learning (ML) models differ in accuracy, computation time, interpretability, and scalability, the very characteristics that are crucial in determining their adequacy for government decision-making. This part presents the comparison of performance of the four models used in this study: ANNs, RF, DTs, and LR.

As reported in Table 7, ANNs yielded the best accuracy in all examined scenarios, and are consequently excellent solutions for complicated forecasting problems, e.g., national budget planning or dynamic healthcare resource estimation. For this, though, ANNs take more time to train and do not possess much interpretability, which might be a handicap in high-transparency policy applications.

TABLE VII. MODEL COMPARISON SUMMARY

Model	Accuracy	Training Time	Interpretability	Scalability	Ideal Use Case
Artificial Neural Network (ANN)	High	High	Low	High	Complex forecasting, national-level policy
Random Forest (RF)	Medium-High	Medium	Medium	High	Real-time systems, emergency resource allocation
Decision Tree (DT)	Medium	Low	High	Medium	Regulatory settings, transparent decision-making
Linear Regression (LR)	Low-Medium	Very Low	High	Medium	Simple trend analysis, high explainability

Random Forests, on the other hand, provide a good compromise between accuracy, interpretability, and training time. This makes them particularly attractive for real-time applications, like emergency logistics, in which it is essential to act fast and reliably. Decision Trees are also quick to train and interpretable which makes it a great candidate for domains that need transparent and auditable approach for decision paths (e.g. regulatory oversight or legal framework). It might not always work well with high dimensional complex datasets though. Lastly, Linear Regression model is the most interpretable and fast model in computations but it's not sophisticated to fit the nonlinear trends. It is most suitable for simple tasks, for example, basic trend analysis or educational performance forecasting, where interpretability is more important than accuracy.
In order to better visualize these trade-offs, we give an overview of model properties in Figure 6 in terms of accuracy, interpretability and training time. This visual encoding supports policy makers and system designers in selecting the model that is best suited for a given public service.

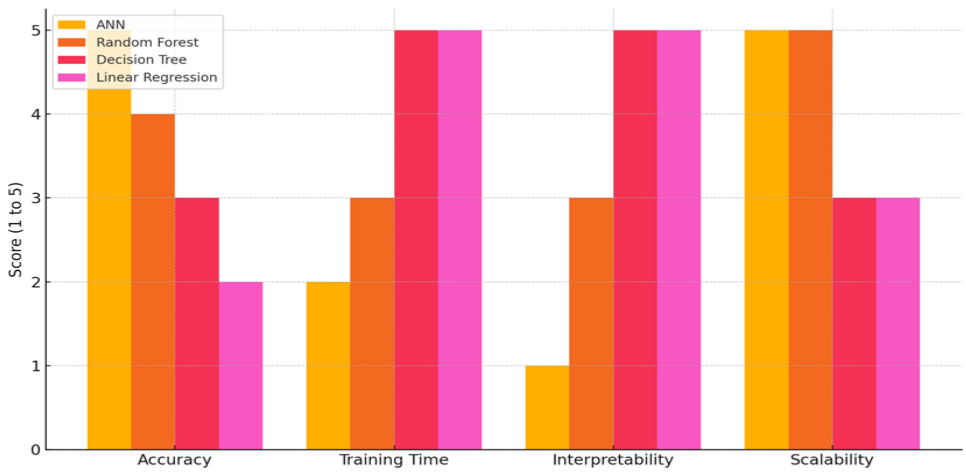

Fig. 6. Comparative Analysis of Machine Learning Models for Governmental Use.

Figure 7: Comparison of four machine learning techniques: (ANN, RF, DT, and LR) across three evaluation criteria – accuracy, training time, and interpretability (1=low, 4=high). ANN has the best prediction accuracy but with poor interpretability and high training cost. Random Forest has a uniform profile: above average behavior for all three measures. The strength of the Decision Trees is that they are very interpretable and very fast, but they have moderate prediction. Linear Regression is fast and transparent, but not sophisticated enough to account for the complicated relationships in the data.

Fig. 7. Model Metrics Comparison.

6. CONCLUSION

The results of this study highlight the potential of ML models as enabling tools for better decision making for the public services of governments in various operational scenarios. We presented our empirical study based on four major models (i.e., Linear Regression (LR), Decision Tree (DT), Random Forest (RF) and Artificial Neural Network (ANN)) and the feasibility of practical algorithms to increase accuracy, timeliness and scalability in the fundamental task in public sector including budget forecasting, healthcare service planning, and emergency resource allocation. ANN proved to be the most accurate model, with the highest accuracy throughout the assessed models, thus being particularly suitable for complex data-rich applications. Random Forest proved to be a powerful a well-balancing model: high prediction abilities and reasonable training efficiency, suitable for on-line systems. At the same time, Decision Trees and Linear Regression were less predictive but had key advantages in terms of transparency, interpretability, and low computational requirements—essential characteristics for decision-contexts that favor explain ability and public accountability. But effective application of ML in governmental systems is about more than just delivering technical performance - aspects like infrastructure readiness, data governance, institutional competence, and ethical considerations should form the focus in order to enable long-term success and public trust. In the next step, research could attempt to embed predictive models within policy feedback loops, to accommodate dynamic policy adjustments based on real-time data. Moreover, Explainable AI (XAI) has to be developed as an interface between complicated models (like ANN) and laymen policymakers, contributing to further transparency and trust. Work on further localization of ML solutions to the governmental structures and cultural peculiarities to a particular region can also aid adoption and effectiveness. Finally, developing strong ethical and legal guardrails for the responsible use of AI in public governance is paramount to protecting fairness, data privacy, and societal values in the era of algorithmic decision-making.

Conflicts of Interest

The author's paper emphasizes that there are no conflicts of interest, either perceived or actual, that could impact the research integrity.

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References

[1] H. Chen, R. H. Chiang, and V. C. Storey, “Business intelligence and analytics: From big data to big impact,” MIS quarterly, vol. 36, no. 4, pp. 1165-1188, Dec. 2012.

[2] X. C. Nguyen et al., “Development of machine learning-based models to forecast solid waste generation in residential areas: A case study from Vietnam,” Resources, Conservation and Recycling, vol. 167, p. 105381, Apr. 2021.

[3] F. Marmolejo-Ramos et al., “AI-powered narrative building for facilitating public participation and engagement,” Discover Artificial Intelligence, vol. 2, no. 1, p. 7, Feb. 2022.

[4] Z. A. Abbood, D. Ç. Atilla, and Ç. Aydin, “Intrusion Detection System through deep learning in routing MANET networks,” Intelligent Automation & Soft Computing, vol. 37, no. 1, 2023.

[5] S. A. A. Bokhari and S. Myeong, “The influence of artificial intelligence on e-Governance and cybersecurity in smart cities: A stakeholder’s perspective,” IEEE Access, vol. 11, pp. 69783-69797, 2023.

[6] S. Chatterjee, “AI strategy of India: policy framework, adoption challenges and actions for government,” Transforming Government: People, Process and Policy, vol. 14, no. 5, pp. 757-775, Nov. 2020.

[7] M. H. Chin et al., “Guiding principles to address the impact of algorithm bias on racial and ethnic disparities in health and health care,” JAMA Network Open, vol. 6, no. 12, p. e2345050, Dec. 2023.

[8] M. Kuziemski and G. Misuraca, “AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings,” Telecommunications policy, vol. 44, no. 6, p. 101976, Jul. 2020.

[9] M. A. Mutawa and H. Rashid, “Comprehensive review on the challenges that impact artificial intelligence applications in the public sector,” in Proceedings of the 5th NA International Conference on Industrial Engineering and Operations Management, 2020, vol. 10, pp. 2078-2087.

[10] Y. Liao, “Investigating prediction performance on regressions models using methods with multiple decision trees,” Ph.D. dissertation, University of Birmingham, Birmingham, UK, 2023.

[11] A. Raza et al., “Ensemble learning-based feature engineering to analyze maternal health during pregnancy and health risk prediction,” PloS one , vol. 17, no. 11, p. e0276525, Nov. 2022.

[12] V. Linardos, M. Drakaki, P. Tzionas, and Y. L. Karnavas, “Machine learning in disaster management: recent developments in methods and applications,” Machine Learning and Knowledge Extraction, vol. 4, no. 2, pp. 272-300, May 2022.

[13] A. Farič and I. Bratko, “Machine Bias: A Survey of Issues,” Informatics, vol. 48, no. 2, 2024.
[14] M. J. Ryan, “Secret Algorithms, IP Rights, and the Public Interest,” Nev. L.J., vol. 21, p. 61, 2020.
[15] Z. A. Abbood, D. Ç. Atilla, Ç. Aydin, and M. S. Mahmoud, “A survey on intrusion detection system in ad hoc networks based on machine learning,” in 2021 International Conference of Modern Trends in Information and Communication Technology Industry (MTICTI) , 2021, pp. 1-8.
[16] C. Min, G. Liao, G. Wen, Y. Li, and X. Guo, “Ensemble Interpretation: A Unified Method for Interpretable Machine Learning,” arXiv preprint arXiv:2312.06255 , Dec. 2023.
[17] S. Aiyar and C. Ebeke, “Inequality of opportunity, inequality of income and economic growth,” World Development, vol. 136, p. 105115, Dec. 2020.
[18] V. Wang and D. Shepherd, “Exploring the extent of openness of open government data–A critique of open government datasets in the UK,” Government Information Quarterly , vol. 37, no. 1, p. 101405, Jan. 2020.