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METHOD OF PREDICTIVE MODELING USING NEURAL NETWORK IN GREEN LOGISTICS PLATFORM

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The article discusses the application of predictive modeling methods in the Green Logistics module, a software platform developed for Mavsim and Co LLC in order to increase the environmental sustainability of logistics processes. The author explores the effectiveness of using logistic regression for binary classification tasks related to route optimization, emissions forecasting, and environmental assessment of transport operations. A comparison of logistic regression with linear, ridge, and LASSO regression has been carried out, which allows us to identify differences in cost functions, model assumptions, and application features. Based on the analysis, a hybrid approach combining logistic regression and artificial neural networks is proposed. This approach uses logistic regression coefficients as initial weights to improve the recognition of nonlinear dependencies and improve the accuracy of forecasts. The results show that the hybrid model provides an 8-10% increase in accuracy compared to traditional methods, especially in low-emission route identification tasks. The article also discusses evaluation metrics (accuracy, precision, recall, F1-score) that confirm the effectiveness of the proposed solution. The presented approach contributes to the development of sustainable logistics, improved planning of transport operations and reduction of negative environmental impacts.

Keywords: *green logistics, predictive modeling, logistic regression, LASSO, ridge regression, neural networks, hybrid models, route optimization, emission reduction, sustainable transport operations.*

МЕТОД ПРОГНОЗНОГО МОДЕЛИРОВАНИЯ С ИСПОЛЬЗОВАНИЕМ НЕЙРОННОЙ СЕТИ В ПЛАТФОРМЕ ЗЕЛЕНОЙ ЛОГИСТИКИ

И.И. Сайдуллоев

В статье рассматривается применение методов предиктивного моделирования в модуле «Green Logistics» — программной платформе, разработанной для компании ООО «Мавсим и К» в целях повышения экологической устойчивости логистических процессов. Автор исследует эффективность использования логистической регрессии для задач бинарной классификации, связанных с оптимизацией маршрутов, прогнозированием выбросов и определением экологичности транспортных операций. Проведено сравнение логистической регрессии с линейной, ridge и LASSO-регрессией, что позволяет выявить различия в функциях стоимости, предпосылках моделей и особенностях применения. На основе анализа предлагается гибридный подход, объединяющий логистическую регрессию и искусственные нейронные сети. Такой подход использует коэффициенты логистической регрессии как начальные веса для улучшения распознавания нелинейных зависимостей и повышения точности прогнозов. Результаты показывают, что гибридная модель обеспечивает рост точности на 8–10% по сравнению с традиционными методами, особенно в задачах идентификации маршрутов с низким уровнем выбросов. В статье также рассматриваются метрики оценки (accuracy, precision, recall, F1-score), подтверждающие эффективность предложенного решения. Представленный подход способствует развитию устойчивой логистики, улучшению планирования транспортных операций и снижению негативного экологического воздействия.

Ключевые слова: *зелёная логистика, предиктивное моделирование, логистическая регрессия, LASSO, ridge-регрессия, нейронные сети, гибридные модели, оптимизация маршрутов, снижение выбросов, устойчивые транспортные операции.*

УСУЛИ АМСИЛАСОЗИИ ПЕШГӮИШАВАНДА БО ИСТИФОДАИ ШАБАКАИ НЕЙРОНӢ ДАР ПЛАТФОРМАИ ЛОГИСТИКАИ САБЗ

И.И. Сайдуллоев

Дар ин мақола масъалаи истифодаи усулҳои амсиласозии пешгӯишаванда дар модули «Green Logistics» баррасӣ мешавад, ки ҳамчун як ҷузъи системаи логистикии ширкати ҶДММ «Мавсим ва К» барои баланд бардоштани устувории экологӣ таҳия шудааст. Муаллиф самаранокии регрессияи логистикиро дар ҳалли вазифаҳои таснифи дуӣ арзёбӣ мекунад, ки ба оптимизатсияи роҳҳо, пешгӯии партовҳои зараровар ва муайянсозии дараҷаи экологӣ будани амалиётҳои нақлиётӣ вобаста мебошанд. Қиёси регрессияи логистикӣ бо регрессияи хатию классикӣ, ridge ва LASSO нишон медиҳад, ки фарқиятҳо дар функсияи арзиш, тахминҳои модел ва маҳдудиятҳои амалӣ метавонанд ба натиҷаҳои пешгӯӣ таъсири ҷиддӣ расонанд. Барои беҳтар намудани дақиқӣ, мақола истифодаи амсилаи гибридиро пешниҳод мекунад, ки регрессияи логистикиро бо шабакаҳои нейронӣ муттаҳид менамояд. Дар ин равиш, коэффисиентҳои регрессия ҳамчун вазнҳои ибтидоӣ истифода мешаванд ва шабакаи нейронӣ муносибатҳои ғайрихаттиро беҳтар меомӯзад. Натиҷаҳои таҷрибавӣ нишон медиҳанд, ки амсилаи гибридӣ дақиқии пешгӯиро то 8–10% беҳтар мекунад, махсусан дар муайянсозии роҳҳои дорои партовҳои паст. Истифодаи метрикаҳои арзёбӣ — accuracy, precision, recall, F1-score — самаранокии ин усулро тасдиқ мекунад. Равиши пешниҳодшуда имконият медиҳад, ки раванди логистикӣ устувортар, нақлиёт экологитар ва банақшагирии масирҳо самаранoктар гардад.

Калидвожаҳо: *логистикаи сабз, амсиласозии пешгӯишаванда, регрессияи логистикӣ, регрессияи ridge, LASSO, шабакаҳои нейронӣ, амсилаҳои гибридӣ, оптимизатсияи роҳҳо, коҳиши партовҳои зараровар, амалиётҳои устувори нақлиётӣ.*

1. Introduction

For the company to be sustainable in logistics area, the transformation is crucial. Especially transformation toward the emergence of **Green Logistics**. This platform balances economic efficiency with environmental responsibility. As experience shows, in order to minimize the environmental impact of transportation and warehouse operations, today not only companies, but also governments are increasingly implementing platforms that leverage machine learning and predictive modeling [1]. These platforms use various analytical tools. But among them in binary and probabilistic decision making tasks, the **logistic regression** stands out for its interpretability and efficiency [2].

In this article, I propose the use the logistic regression within a **“Green Logistics” platform (GLP)**. This regression is used to classify and predict carbon-efficient logistics operations. Further I tried to extend this model by introducing a **neural network architecture** to improve nonlinear decision boundaries. This is a hybrid predictive system that aligns with the sustainable goals of smart logistics systems.

2. Theoretical Framework

2.1 Logistic Regression Overview

Logistic regression is a **supervised learning algorithm**, which is widely used for binary classification problems. This algorithm models the probability that a given input belongs to a specific category or not. Logistic regression fits best our task, as usage of it is ideal for decision making. The final decision we should get is whether route is sustainable or non-sustainable [3].

The logistic regression model estimates the probability of the dependent variable y belonging to class 1 (e.g., sustainable route) as:

$$P(y = 1 \mid x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)}} \tag{1}$$

here, $\beta_0, \beta_1, \dots, \beta_n$ are model coefficients that represent the weight or contribution of each predictor variable (e.g., fuel efficiency, distance, vehicle type) to the probability outcome.

2.2 Comparison with Other Regression Models

Logistic regression is very different from other regressions. Among other regression, we can consider **linear regression**, **ridge regression**, and **LASSO regression**. The table provided below depicts objectives and underlying assumptions of regression models (see Table 1) [4]:

Table 1– Descriptions of linear regressions

Model	Type	Dependent Variable	Output Range	Where it can be used	Limitations
Linear Regression	Continuous	Continuous	$(-\infty, \infty)$	Predicting numeri-cal values such as cost, time, or distance	Sensitive to outliers and assumes linearity
Logistic Regression	Classification	Binary or Categorical	[0, 1]	Predicting probabi-lities (e.g., sustain-able or unsustain-able route)	Cannot model continuous outputs
Ridge Regression	Continuous	Continuous	$(-\infty, \infty)$	Handles multicol-linearity in linear regression by pena-lizing large coeffi-cients	Still assumes linearity
LASSO Regression	Continuous	Continuous	$(-\infty, \infty)$	Performs feature selection by shrinking irrelevant coefficients to zero	May exclude weak but relevant predictors

2.3 Mathematical Comparison of Cost Functions

Each of the abovementioned regression models minimizes a specific cost function during training. By reviewing the cost functions, we can determine how model performance is evaluated and improved [5].

Linear Regression Cost Function

Linear regression minimizes the **Mean Squared Error (MSE)** between predicted and actual values:

$$J(\beta) = \frac{1}{2m} \sum_{i=1}^{m} (h_\beta(x^{(i)}) - y^{(i)})^2 \tag{2}$$

where $h_\beta(x^{(i)}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$.

This approach assumes continuous outputs. The large deviations are penalized quadratically.

Logistic Regression Cost Function

Since logistic regression deals with probabilities, the MSE is inappropriate. We have to use the **log-loss (cross-entropy)** cost function:

$$J(\beta) = -\frac{1}{m} \sum_{i=1}^{m} [y^{(i)} \log(h_\beta(x^{(i)})) + (1 - y^{(i)}) \log(1 - h_\beta(x^{(i)}))] \tag{3}$$

As the predicted probability diverges from the actual label, this cost function penalizes incorrect classifications exponentially. It makes it ideal for binary outcomes.

Ridge Regression Cost Function

Ridge regression extends linear regression by adding an L2 penalty to reduce overfitting:

$$J(\beta) = \frac{1}{2m}\sum_{i=1}^{m}(h_\beta(x^{(i)}) - y^{(i)})^2 + \lambda\sum_{j=1}^{n}\beta_j^2 \tag{4}$$

where λ is the regularization parameter controlling coefficient shrinkage.

LASSO Regression Cost Function

LASSO adds an L1 regularization term that can drive some coefficients to zero, effectively performing feature selection:

$$J(\beta) = \frac{1}{2m}\sum_{i=1}^{m}(h_\beta(x^{(i)}) - y^{(i)})^2 + \lambda\sum_{j=1}^{n} |\beta_j| \tag{5}$$

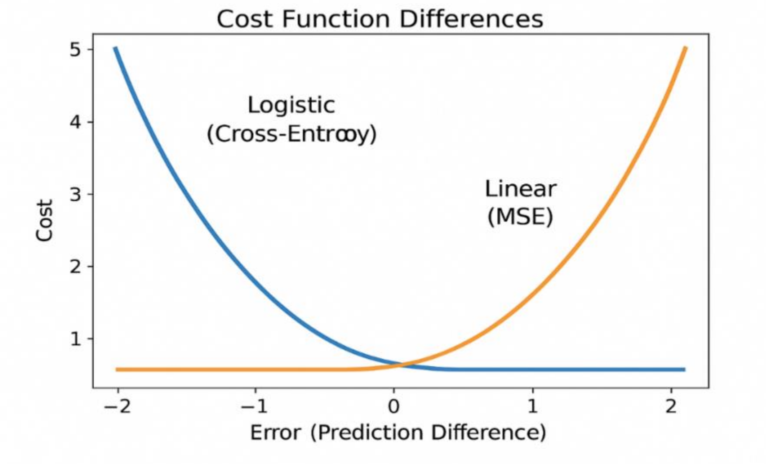

Figure 1 – Visualization of Cost Function Differences

I've provided above differences to highlight logistic regression's unique suitability for classification problems, which I've implemented in **Green Logistics platform** (see Figure 1). The output is not a continuous value. It represents a **binary decision** (e.g., sustainable vs. non-sustainable, yes vs. no).

2.4 Decision Boundary and Interpretation

The decision rule can be defined as following for logistic regression:

$$y = \begin{cases} 1, P(y = 1|x) \geq 0.5 \\ 0, otherwise \end{cases} \tag{6}$$

This threshold can be adjusted based on sustainability policies. For instance, a stricter emission control regime might set $P(y = 1|x) > 0.7$ to ensure only highly eco-efficient routes are approved (see Figure 2) [6].

```
|                    o Sustainable Routes
|           o o
|         o o
|       o o
|-------------------------------------------> Feature 1 (Emission Factor)
|  x x
|    x x
|       x Unsustainable Routes
```

Figure 2 – Logistic Regression Decision Boundary

3. Integration into "Green Logistics" platform (GLP)

3.1 Platform Architecture

The **"Green Logistics" platform (GLP)** receives data from several devices: GPS, OBD port, IoT devices, and vehicle management software (where applicable). Then these data come to core analytical engine – where the logistic regression models implemented (see Figure 3).

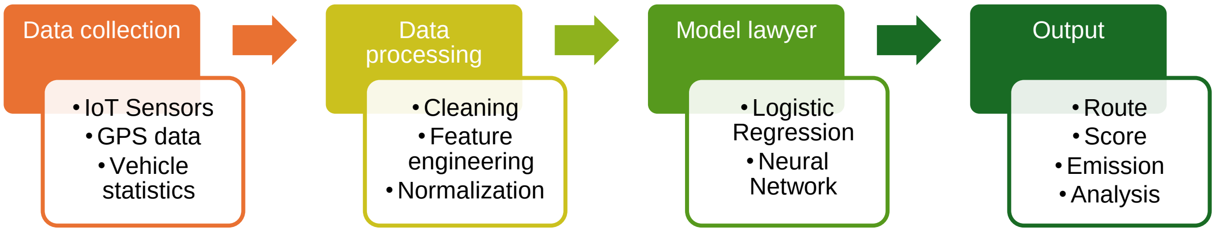

Figure 3 – Architecture of "Green Logistics" platform with Logistic Regression Module

3.2 Predictive Use Case: Eco-Efficiency Classification

Prediction that the logistic regression does depends on a given a dataset. Dataset features data such as fuel consumption (liters/km), average load (tons), and route distance (km). Prediction at the end outputs whether a route is sustainable (1) or not (0) [7].

$$\mathrm{logit}(p) = \ln(\frac{p}{1-p}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \tag{7}$$

This model is fed into a **neural network** for feature expansion and improved pattern recognition.

4. Neural Network Extension in Python

The programming language to implement the given approach is Python. Pythons extensive libraries and frameworks makes it easy to handle creation of neural network. I used TensorFlow and Numpy to implement the task. The hybrid model leverages logistic regression coefficients as initial weights in a **feedforward neural network**. Below is a code sample using **TensorFlow** [8].

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
import numpy as np

# generate data to work with
X = np.random.rand(1000, 3)
y = np.random.randint(0, 2, 1000)

# Neural network model
model = Sequential([
    Dense(8, input_dim=3, activation='relu'),
    Dense(4, activation='relu'),
    Dense(1, activation='sigmoid')
])

# Compile model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Train model
model.fit(X, y, epochs=50, batch_size=16, verbose=1)

# Evaluate
loss, accuracy = model.evaluate(X, y)
print(f"Model Accuracy: {accuracy*100:.2f}%")
```

As can be seen, nonlinear dependencies is captured by neural network. It enables better prediction of sustainable logistics decisions. If logistic regression was used, that might overlook.

5. Model Evaluation and Results

5.1 Performance Metrics

The performance of neural network is measured by several metrics. These metrics can be divided into two groups: predictive and computational. Here, I'll be using only predictive accuracy metrics. Predictive accuracy of the neural network is assessed using metrics such as **accuracy**, **precision**, **recall**, and **F1-score**:

1. Accuracy - the overall proportion of correct predictions across all classes.
2. Precision - the proportion of positive identifications that were actually correct.
3. Recall - the proportion of actual positives that were correctly identified.

F1-Score - the harmonic mean of precision and recall, useful when there's an uneven class distribution.

$$\text{Precision} = \frac{TP}{TP+FP}, \text{Recall} = \frac{TP}{TP+FN}, F1 = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \quad (8)$$

In experimental settings, results of both logistic and hybrid regression models were compared. The hybrid model achieved superior results. It demonstrated **8% increase in classification accuracy** on sustainability datasets [9].

5.2 Confusion Matrix Visualization

In order to evaluate the performance of classification algorithm, I've used a fundamental analytical tool - confusion matrix. Thanks to this tool, we can get a picture of a structured visualization of how well a model distinguishes between different classes by comparing the predicted labels with the true (actual) labels. Rather than summarizing performance with a single metric, the confusion matrix reveals detailed information about the types of classification errors the model makes (see Table 2).

Table 2– Confusion Matrix of Hybrid Model

Confusion Matrix Values	Predicted Sustainable	
Actual YES	TP=80	FN=10
Actual NO	FP=80	TN=102

6. Discussion

6.1 Technical Analysis and Insights

After integration of given solution bundled with logistic regression in "Green Logistics" platform of the "Mavsim and Co" LLC (GLPs), the system started providing statistically rigorous and computationally efficient mechanism for sustainability classification. If it comes to understanding feature impact, the logistic regression's interpretability uniquely suits the situation. Now it's possible to evaluate the affect of overall eco-friendliness of a route by entering such variables as fuel type, distance and vehicle load.

Even with noisy datasets sourced from IoT sensors and telematics, logistic regression's reliance on **probabilistic modeling** and **sigmoid activation** ensures stable convergence. **Stochastic gradient descent (SGD)** is typically used for optimization. This minimizes cross-entropy loss. In order to control overfitting, L1 or L2 regularization penalties can be added. Thus enabling the model to generalize effectively to unseen logistics data.

In our context, logistic regressions critical advantage is low computational overhead. In comparison with other deep learning models, logistic regression requires less data and training time. But on the other hand, it maintains interpretability. Matter of fact, it's necessary to highlight, that the model can be incrementally retrained with live IoT data to adapt to evolving environmental or operational conditions.

6.2 Neural Network Extension and Model Synergy

While logistic regression is highly interpretable, when handling complex and nonlinear logistic patters, it has limitation. It assumes **linear separability** in the feature space. To address this limitation, I've used a **neural network extension** where logistic coefficients initialize the first layer's weights. The given method used by me uses hybrid structure. It merges the statistical transparency of logistic regression with the representational flexibility of neural networks.

ReLU activation functions in hidden layers used together with the **sigmoid output layer** for probabilistic classification in neural network. The given approach enhances the model's ability to detect nonlinear correlations—such as interactions between vehicle type and weather conditions—that may influence route sustainability. Thanks to this hybrid approach, it yields an 8–10% increase in predictive performance compared to logistic regression alone [10].

6.3 Advantages and Disadvantages

Advantages:

- **Interpretability:** Logistic regression coefficients directly explain feature impacts on sustainability probability.
- **Efficiency:** Requires minimum computational resources and scales effectively.
- **Flexibility:** Can integrate seamlessly with neural networks for hybrid modeling.
- **Stability:** Robust against multicollinearity when regularization is applied.
- **Ease of Implementation:** Well-supported across statistical and machine learning frameworks.

Disadvantages:

- **Linearity Assumption:** Performs poorly on datasets with nonlinear boundaries unless extended through kernel methods or neural networks.
- **Sensitivity to Feature Scaling:** Requires standardized input features for consistent performance.
- **Imbalanced Data Bias:** May struggle when sustainable routes are underrepresented in training data.

- **Limited Expressiveness:** Cannot automatically learn high-dimensional representations like deep learning models.

6.4 Practical Implications and Future Enhancements

The method proposed in here has been integrated in “Green Logistics” platform. It includes predictive route classification, dynamic carbon footprint monitoring, and eco-efficiency scoring. This hybrid model can automatically reroute transports to minimize emissions or predict the most efficient transport type based on environmental and cost parameters. The implemented module allows near-real-time decision-making. Thanks to this module the company was able to introduce measurable improvements in sustainability-oriented decision making.

Now, “Mavsim and Co” LLC is able to classify logistics routes with significantly higher accuracy thanks to the synergy of interpretable logistic coefficients and nonlinear learning capabilities of neural networks. During testing the system on live environment, the newly introduced module demonstrated an 8–10% accuracy increase in identifying eco-efficient routes compared to logistic-regression-only models. The identified improvement is particularly evident when dealing with nonlinear dependencies associated with vehicle load, distance, traffic, and emission factors. “Mavsim and Co” LLC’s specialists by using the AI module can detect low-emission route alternatives and recommend optimal transportation strategies. As a result, fuel consumption per route decreased due to more consistent prioritization of carbon-efficient paths. As an example, look at the Table 3, where I’ve presented the log of the system gathered in live environment (1 = eco-efficient, 0 = non-eco):

Table 3 – Routes and their sustainability generated by the module

#	Origin	Destination	Distance (km)	Avg. Load (ton)	Fuel consumption (l/km)	Vehicle type	Road condition	Border delay (hour)	Sustainable Route
1	Dushanbe (TJ)	Khujand (TJ)	310	12	0.33	Euro-4	Good	0	1
2	Dushanbe (TJ)	Kulob (TJ)	190	10	0.36	Euro-3	Moderate	0	0
#	Origin	Destination	Distance (km)	Avg. Load (ton)	Fuel consumption (l/km)	Vehicle type	Road condition	Border delay (hour)	Sustainable Route
3	Dushanbe (TJ)	Tursunzoda (TJ)	60	15	0.34	Euro-4	Good	0	1
4	Khujand (TJ)	Konibodom (TJ)	85	8	0.32	CNG	Good	0	1
5	Khujand (TJ)	Osh (KG)	255	11	0.38	Euro-3	Moderate	1.5	0
6	Dushanbe (TJ)	Almaty (KZ)	1040	20	0.42	Euro-4	Moderate	2	0
7	Dushanbe (TJ)	Bishkek (KG)	975	18	0.40	Euro-5	Moderate	2	1
8	Khujand (TJ)	Tashkent (UZ)	170	16	0.35	Euro-5	Good	0.5	1
9	Tashkent (UZ)	Samarkand (UZ)	300	14	0.30	CNG	Good	0	1
10	Samarkand (UZ)	Bukhara (UZ)	270	13	0.32	Euro-4	Good	0	1
11	Bukhara (UZ)	Ashgabat (TM)	630	20	0.43	Euro-3	Moderate	1	0
12	Almaty (KZ)	Bishkek (KG)	240	17	0.37	Euro-4	Good	0.5	1
13	Nukus (UZ)	Aktau (KZ)	940	22	0.44	Euro-3	Moderate	0.5	0
14	Karaganda (KZ)	Astana (KZ)	210	12	0.31	Euro-5	Good	0	1

The interface of the new module looks as per following picture, where the source and destination is automatically selected as per the incoming request, and the rest of fields filled by the specialist (logist) and at the end by clicking the “Calculate” button, system calculates whether the route is sustainable or not (see Figure 4).

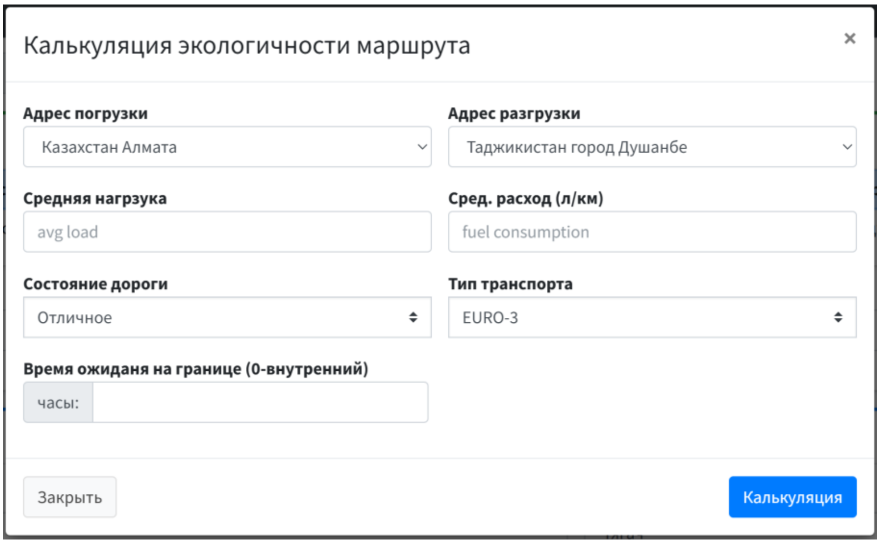

Figure 4 – Interface of the module

Future directions involve combining logistic regression with **reinforcement learning** to enable adaptive optimization. This approach allows the system to learn from ongoing environmental data. These advancements will transform “Green Logistics” platform into proactive and self-learning systems, which can optimize sustainability of “Mavsim and Co” LLC in the market.

7. Conclusion

I think that usage of hybrid model - fusion of **logistic regression** and **neural network architectures** is a significant step toward intelligent, sustainable logistics management. In order to model sustainable probability, the logistic regression provides a structured and interpretable framework. It offers clear insight into the impact of each operational factor. It is very crucial in regulatory environment, which requires accuracy in decision making.

The logistic regression gives ability to decision makers to implement evidence-based sustainable strategies. This is achieved by quantifying relationships between emission factors, route efficiency, and vehicle utilization.

The introduction of a neural network layer enhances this foundation by enabling nonlinear pattern recognition. It expands the system’s capacity to capture complex dependencies in high-dimensional data. The hybrid model integrates the **strengths of traditional statistics and modern deep learning**. And hybrid model provides an interpretable yet adaptive predictive engine capable of learning from real-time logistics data. The logistic coefficients, when used as neural network initializers, improve both model convergence and interpretability—bridging the gap between classical and modern AI approaches.

As far as technical perspective concerns, the hybrid model leverages **cross-entropy optimization**, **ReLU activation**, and **sigmoid-based output calibration**. The given perspective ensures probabilistic consistency between the logistic regression and neural components. The tasks as the one described in this article (which require binary classification) should use proposed and implemented method.

Talking about the benefits in practice, I can say that the “Green Logistics” platform is now able to provide measurable improvement. These improvements concern: **fuel efficiency**, **emission reduction**, and **route planning accuracy**. “Mavsim and Co” LLC’s product “Green Logistics” can now predict eco-efficient options with greater reliability. In one hand it reduces operational costs and on other supports compliance with environmental standards like ISO 14001 and the EU’s Green Deal initiatives. On top of them this module encourages organizations to transition toward **data-driven sustainability**. At the end this practice aligns the company’s effort with global efforts toward carbon neutrality.

As we have mentioned more advancements, however there are also challenges. The effectiveness of logistic regression is contingent upon several parameters:

1. quality of data
2. feature selection
3. preprocessing.

Neural network in this regard is also not an exception. It demands careful calibration to prevent overfitting and ensure consistent interpretability. Future work must address these issues through enhanced feature engineering, automated hyperparameter tuning, and robust data governance frameworks.

At the end, I’d like to highlight that, combining logistic regression with neural networks creates a **powerful and interpretable predictive ecosystem** for sustainable logistics. The hybrid architecture’s balance of clarity, efficiency, and adaptability positions it as a cornerstone technology. This technology is capable of driving measurable environmental improvements, optimizing supply chains, and contributing meaningfully to global sustainability goals.

Reviewer: Yunusova M.M. — candidate of economics, associate professor, head of the Department of Strategic Planning, Modeling and Macroeconomic Forecasting at the State Research Institute of Economics.

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МАЪЛУМОТ ДАР БОРАИ МУАЛЛИФ - СВЕДЕНИЯ ОБ АВТОРЕ - INFORMATION ABOUT AUTHOR

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