An Intelligent Method of Prediction the Demand for Goods/Services in Crisis Conditions

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Abstract

This study presents the development of a method for prediction the demand for goods and services in crisis conditions, with an emphasis on intelligent algorithms and adaptation to changing market conditions. Noting the limitations of existing approaches, which are mainly focused on specific sectors or have high complexity, this study makes a significant contribution by integrating forecast data to improve the accuracy of further prediction. The method covers the full cycle from data collection and integration to analysis of its performance using advanced machine learning techniques such as HistGradientBoostingRegressor and XGBoost. The RMSE and MAE values indicate the high accuracy of our method compared to other studies using different metrics. The project chosen for the practical implementation of the method demonstrates its effectiveness in real conditions, confirming its importance in various sectors of the economy. The high level of adaptability and accuracy makes the method particularly valuable for resource management in various economic sectors, surpassing other less comprehensive approaches.

Keywords

Demand prediction, Economic crisis, Intelligent algorithms, Machine learning

1. Introduction

In today's dynamic world, where market conditions change rapidly, especially in the context of economic and social crises, the ability to accurately prediction the demand for goods and services becomes critical. This not only helps businesses and organizations to effectively plan their activities, but also contributes to the stability of the economy as a whole. Accordingly, the development of effective prediction methods that can adapt to rapid changes in consumer demand and market conditions becomes an important task.

Traditional prediction methods are often challenged by changing market conditions, especially during crises. This includes insufficient flexibility and adaptability to new data, as well as a limited ability to take into account the complexity and unpredictability of human behavior and economic processes. Therefore, there is a need to develop more advanced, intelligent prediction methods that can work effectively under a wide range of conditions, including periods of economic uncertainty.

The purpose of this paper is to develop an intelligent method of demand prediction for goods and services, particularly in times of crisis. The method is distinguished by its ability to integrate

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prediction data to improve the accuracy of future predictions. This approach not only ensures high accuracy and adaptability, but also opens up new opportunities for flexible response to market challenges.

The rest of paper is structured as follows. In the "Related Work" section, an analysis of modern existing methods in the domain was carried out. Next, the "Method" section presents the developed method in detail, including the stages of data collection, their processing, selection of the optimal prediction model, and its analysis. The section "Case Study" describes the experimental part of th paper. Finally, the "Conclusion" section summarizes the key aspects of the research and its practical significance.

2. Related Work

The study [1, 24] uses a complex deep learning approach based on LSTM networks for demand analysis in the field of supply chain management. This method, although effective, requires significant computing resources and is highly complex. At the same time, studies [3] and [4] focus on the use of machine learning to demand prediction in specific areas - taxis and agriculture, respectively. These methods are limited in their specificity and are not widely used.

Work [2] analyzes changes in consumer behavior during the economic crisis. However, the lack of specific prediction algorithms makes this research less practical for real-world application. On the other hand, studies [5] and [6] focus on narrow market segments, such as financial time series and the labor market. These techniques, while useful in their own domains, cannot be easily adapted to other sectors. Also, works [7] and [8] consider specialized models for the demand prediction for food additives during a pandemic and in the field of water-energy connection. These studies also have limitations due to their specificity.

The study [9] analyzes the application of machine learning methods for predicting the number of patients in emergency medical institutions. The main limitation of this approach is its narrow specialization, which prevents its use in other areas.

The article [10] presents a methodology for prediction of short-term time series, but it does not involve using already predicted data for further predictions. This approach is more focused on mathematical modeling and the use of specific techniques for high-dimensional data, while our method covers a wider range of data sources and includes a more detailed preparation and visualization process.

Work [11] describes the use of a multimodal neural network for sales volumes prediction, but does not focus on the use of prediction data as a basis for subsequent predictions. This method differs from ours by using specific external data, such as Google news and trends, and focusing on neural networks, while our approach is more versatile and open to different machine learning techniques.

The studies analyzed above cover a wide range of demand prediction methods, from specific fields such as supply chain management, agriculture, and healthcare, to more general approaches that use machine learning to analyze financial time series and the labor market. However, none of these studies include the use of predicted data as a basis for further prediction, which is a key feature of our method.

Thus, the goal of our work is to develop a method of intelligent prediction of the demand for goods/services in crisis conditions, which includes the use of predicted data to increase the accuracy of further predictions. This allows our method to be more flexible and adaptable to different scenarios, unlike analogs [10, 11], which do not take into account this important aspect of prediction.

3. Method

In today's world, where data is a critical resource for making informed business decisions, time series prediction plays a key role. This is especially important in conditions where market variability and customer needs are constantly evolving, especially in times of crisis. Effective data analysis and prediction not only enables a better understanding of current trends, but also predicts future changes, which is extremely valuable for strategic planning and resource optimization. In this context, an intelligent method of prediction the demand for goods/services in crisis conditions (Fig. 1) has been developed, which covers from the selection and preparation of data to the determination of the optimal prediction model and visualization of results.

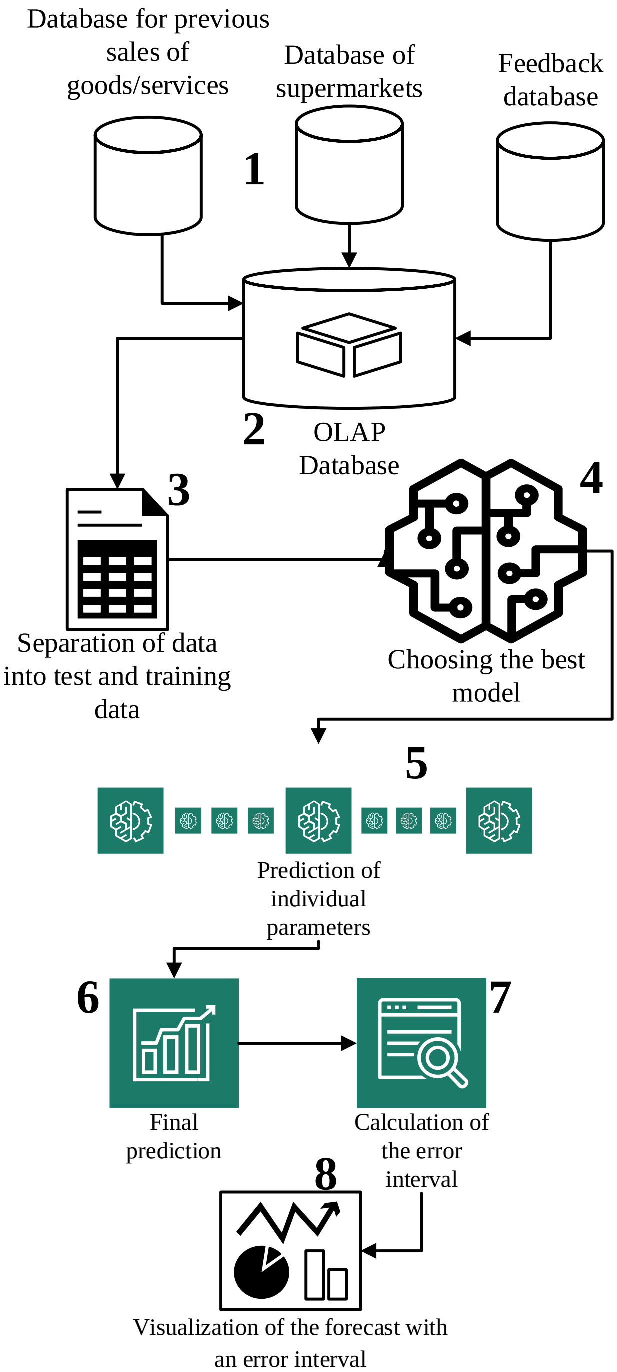

Figure 1: The structure of the intelligent method of demand prediction for goods/services in crisis conditions

The description of the intelligent method of prediction the demand for goods/services in crisis conditions is presented by the following stages:

Stage 1: Data collection (Block 1): collection of customer reviews from various online sources; data from retail points; historical sales data for previous periods.

Stage 2. Data integration and preparation (Block 2): combining data in the OLAP [12] database to improve structuring; data cleaning, normalization and transformation before analysis. We denote the data set as D, where $D=\{d_1, d_2,..., d_n\}$ and each element di contains parameters:

- Time t,
- Number of services/goods s,
- Sales of services/goods p,
- Positive feedback about *fps* services/products,
- Negative feedback about *fns* services/goods.

Stage 3. Separation of data (Block 3).

3.1. Creation of training and test sets. The data is divided into training and test sets, usually based on time intervals to ensure objectivity of the evaluation.

Training set: $Dtrain = \{d_1, \dots, d_{t-0.2\times t}\}$.

3.2. Determination of the period of training and testing. Historical data for a certain period is used for training, and recent data is used for testing.

Test set: $Dtest = \{d_{t-0.2\times t}, \dots, dt\}$.

Stage 4. Selection of the best model for prediction time series (Block 4).

4.1 Study of different models. Review of various machine learning models, in particular, ensemble methods, as well as specialized models for time series. Consider a set of models $Dtest = \{d_{t-0.2\times t}, \dots, dt\}$, where each mi is a potential model for prediction.

4.2. Cross-validation and evaluation of models. For each mi model, we perform cross-validation on *Dtrain* and calculate metrics such as RMSE, MAE [13]. The selection of the best mbest model is based on the minimization of these metrics.

Stage 5. Building a comprehensive prediction

5.1. Training of the selected model (Block 5). Using *m*best to predict individual parameters $\hat{p}, \hat{f}_{ps}, \hat{f}_{ns}, \hat{f}_{pp}, \hat{f}_{np}$ on *D*test.

5.2. Integration of prediction (Unit 6). Use of predicted values of key parameters to form the final prediction. Combining predictions of individual parameters to build the final prediction $\hat{s}_{final}$ of the number of services.

Stage 6. Calculation of the error interval (Block 7).

6.1. Application of the Bootstrap Method [14]: Creation of several variants of B training sets to evaluate the stability of the *Dtrain* model.

6.2. Calculation of the reliability interval based on the distribution of predictions $\{\hat{s}^{(b_1)}, \dots, \hat{s}^{(b_B)}\}$.

Stage 7. Visualization of the prediction with an error interval (Block 8).

7.1. Visualization of actual s and predicted $\hat{s}_{final}$ values.

7.2. Display of actual s and predicted $\hat{s}_{final}$ values.

7.3. Representation of the confidence interval as a shaded area around $\hat{s}_{final}$

4. Case Study

As part of the study, the "SmartMed" project was chosen, which is aimed at developing innovative medical solutions in the context of smart cities. The project covers a wide range of activities, including telemedicine, medical data analysis and intelligent recommendations for health support.

The main emphasis in this study was on the development of an intelligent forecasting system (Fig. 2) capable of adapting to changes in the market, especially during periods of crisis. The initial forecasting stage involved gathering data from a variety of sources, such as online reviews [19, 21] and medical product sales statistics, as well as historical data.

Using data analysis, key parameters for forecasting were determined, including: paracetamol sales, positive feedback about the service, negative feedback about the service, positive feedback on paracetamol, negative feedback on paracetamol, number of services. Based on the RMSE and MAE [25] criteria, the HistGradientBoostingRegressor [15] model was selected as the most accurate for predicting these parameters. The results of the comparison of this model with other machine learning algorithms are shown in Table 1.

Table 1
Model evaluation results

Parameter Head 1	HistGradientBoosting Regressor [15]		XGBoost [16]		CatBoost [17]		LightGBM [18]	
	RMSE	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**
paracetamol sales	10.2	8.6	11.2	9.3	15.3	9.7	11.2	12.5
positive feedback about the service	12.3	10.1	22.3	20.3	34.4	39.1	11.2	12.4
negative feedback about the service	14.8	11.9	12.2	13.9	12.3	14.9	15.3	13.2
positive feedback on paracetamol	7.2	6.5	22.3	26.5	34.2	37.6	35.2	34.2
negative feedback on paracetamol	13.5	10.8	16.6	18.9	53.4	60.5	53.2	62.3
number of services	9.5	8.2	19.5	28.2	59.1	45.9	39.1	48.7

The XGBoost method [16] was used to predict the "number of services" parameter, which demonstrated higher accuracy according to R2 (Table 2) [20, 22]. Taking into account the received forecasts and their interrelationships, the final forecast for "number of services" was formed (Fig. 2).

Table 2
Accuracy for "number of services" R^2 [20] relative to other parameters

Model	R^2
HistGradient BoostingRegressor	0,91
XGBoost	0,98
CatBoost	0,89
LightGBM	0,85

Next, the model was built and the accuracy of the model was analyzed using the RMSE and MAE indicators, which confirmed its effectiveness (Fig. 2). The RMSE value was approximately 10.35, indicating the root mean square error, and the MAE, which was 8.97, reflected the mean absolute error of the forecasts.

Therefore, the results of the study indicate the practical applicability of the proposed approach to forecasting within the "SmartMed" project, in particular for increasing the efficiency of resource management in the field of health care.

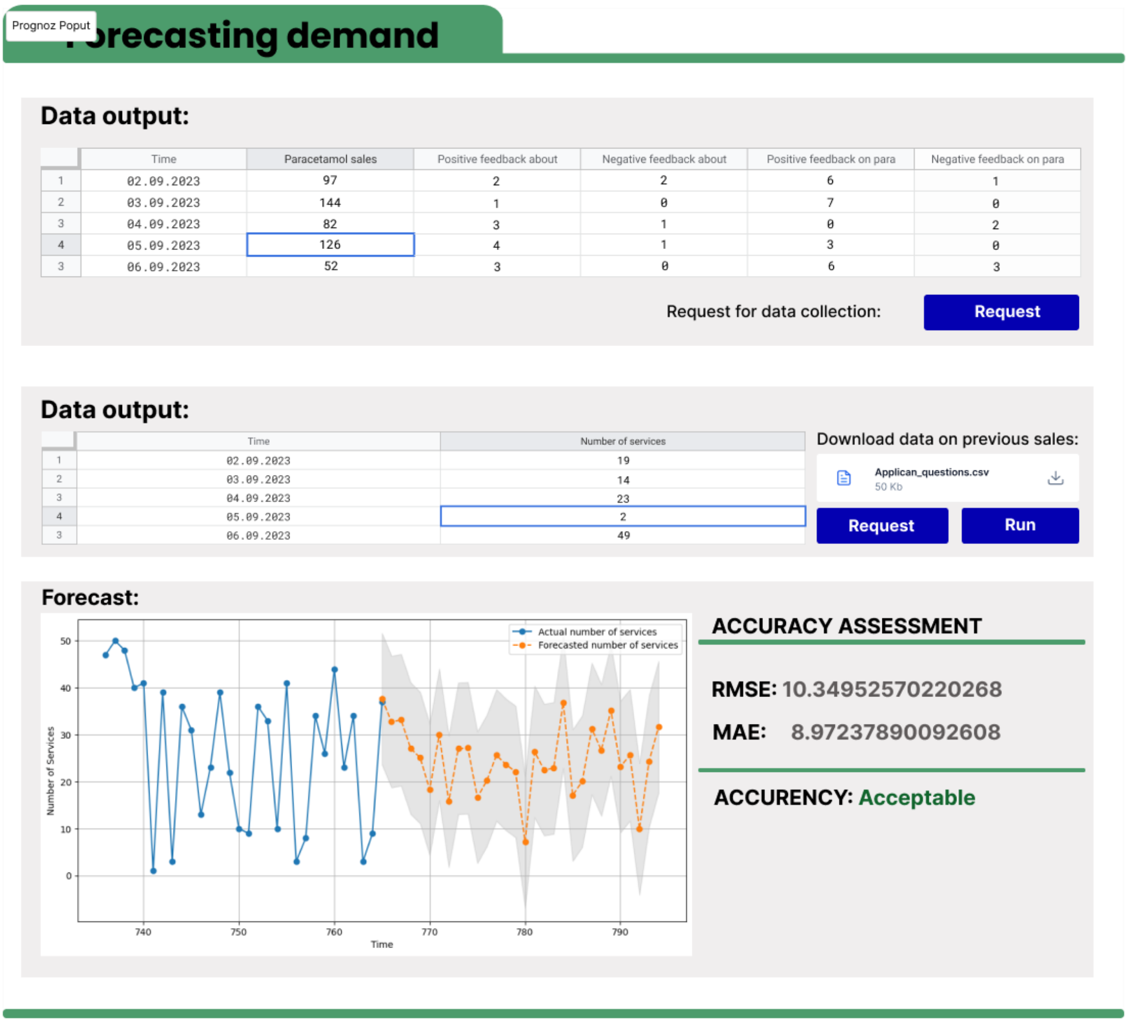

Figure 2: Window of intelligent demand forecast

To compare the results of our study with the results of similar studies [10] and [11], a Table 3 is presented that includes the main characteristics of each approach.

Table 3
Comparison of similar studies

Features	Our method	Research [10]	Research [11]
Methods of machine learning	HistGradientBoostingRegressor, XGBoost, CatBoost, LightGBM	TRMF, BTMF	Neural networks (Filternet)
Accuracy estimates	RMSE ~10.35, MAE ~8.97, R2 до 0.98	sMAPE 8.22, MASE 0.49, OWA 0.58	Value z −3.1733, p-value 0.00152
Analysis of accuracy estimates	High accuracy and reliability in predicting various health parameters	Competitive results in short-term time series forecasting	Confirmation of the statistical significance of improved forecasts during specific events
Efficiency [23]	High adaptability and accuracy in various health scenarios, ability to quickly adapt to changes in the market	Efficiency in forecasting using matrix factorization, good processing of short-term time series	High efficiency in forecasting during crisis events, ability to integrate additional data to improve accuracy

When comparing the accuracy estimates of the three studies, it can be seen (Table 1) that each of them uses different metrics, but all demonstrate high accuracy in their measurements. Our method shows low values of RMSE (~10.35) and MAE (~8.97) and high R2 (up to 0.98), indicating its high accuracy. Study [10] uses sMAPE (8.22), MASE (0.49) and OWA (0.58), showing good accuracy with these composite metrics. Research [11] demonstrates the statistical significance of its results with a low p-value (0.00152) and z-value (−3.1733). This highlights that although the metrics differ, each approach effectively measures prediction accuracy in its context.

Our method stands out due to its ability to adapt to changes in the market, especially during periods of crises, and the use of various data sources for accurate forecasting. It demonstrates high accuracy with low RMSE and MAE values and a high coefficient of determination R2. This makes our method particularly effective for resource management in any sector of the economy, giving it an advantage over other methods that may be limited in their specificity or use less complex forecasting approaches.

5. Conclusions

The developed intelligent method is distinguished by its unique ability to adapt to market crisis scenarios. This approach integrates the analysis of forecast data, significantly increasing the accuracy of future forecasts. This possibility separates this method from traditional studies [10, 11], which are often limited by their specificity and do not take into account the dynamics of changes over time.

The proposed method shows low values of RMSE (~10.35) and MAE (~8.97) and high R2 (up to 0.98), indicating its high accuracy. Compared with studies [10] and [11], our method demonstrates competitive accuracy by using different machine learning methods and showing high adaptability.

The method can be applied in various areas of the economy, in particular to increase the efficiency of resource management in crisis conditions. Its flexibility and adaptability open wide prospects for further development and application in other sectors, adapting to new market conditions.

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