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A COMPARATIVE ANALYSIS OF MACHINE LEARNING METHODS WITH THE APPLICATION OF THE KOLMOGOROV-GABOR POLYNOMIAL FOR FORECASTING SPORTS EVENT OUTCOMES

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Abstract. The article presents a comparative analysis of the effectiveness of machine learning methods for predicting the results of football matches, with a focus on the application of the elementary image of the Kolmogorov-Gabor polynomial. The relevance of the study is due to the need to choose models that are balanced in accuracy, interpretability, and computational complexity in conditions of high stochasticity of sports data. The scientific novelty lies in the adaptation of the elementary image of the Kolmogorov-Gabor polynomial (KGp) for sports analytics tasks and its complex comparison with a wide range of algorithms, from classical regression to gradient boosting. Based on historical data, models have been built and analyzed: an elementary image of a polynomial, linear regression with regularization, a random forest, gradient boosting, and a neural network. The results were evaluated by metrics MAE and accuracy of predicting the outcome. A model based on an elementary image of a polynomial Kolmogorov-Gabor showed competitive accuracy comparable to more complex ensemble methods, while maintaining advantages in computational efficiency and the potential interpretability of the structure of nonlinear dependencies. It was concluded that it is advisable to use this approach as an effective tool for building hybrid forecasting systems in sports analytics.

Keywords: comparative analysis, prediction of results, football, elementary image of the Kolmogorov-Gabor polynomial, machine learning, sports analytics, gradient boosting, random forest, neural network, regression analysis

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СРАВНИТЕЛЬНЫЙ АНАЛИЗ МЕТОДОВ МАШИННОГО ОБУЧЕНИЯ С ПРИМЕНЕНИЕМ ПОЛИНОМА КОЛМОГОРОВА-ГАБОРА ДЛЯ ПРОГНОЗИРОВАНИЯ РЕЗУЛЬТАТОВ СПОРТИВНЫХ СОБЫТИЙ

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Аннотация. В статье представлен сравнительный анализ эффективности методов машинного обучения для прогнозирования результатов футбольных матчей, с фокусом на применении элементарного образа полинома Колмогорова-Габора. Актуальность исследования обусловлена необходимостью выбора сбалансированных по точности, интерпретируемости и вычислительной сложности моделей в условиях высокой стохастичности спортивных данных. Научная новизна заключается в адаптации элементарного образа полинома Колмогорова-Габора для задач спортивной аналитики и его комплексном сравнении с широким спектром алгоритмов — от классической регрессии до градиентного бустинга. На основе исторических данных построены и проанализированы модели: элементарный образ полинома, линейная регрессия, случайный лес, градиентный бустинг и нейронная сеть. Результаты оценивались по метрикам MAE и точности предсказания исхода. Модель на основе элементарного образа полинома Колмогорова-Габора (пКГ) показала конкурентную точность, сопоставимую с более сложными ансамблевыми методами, при этом сохранив преимущества в вычислительной эффективности и потенциальной интерпретируемости структуры нелинейных зависимостей. Сделан вывод о целесообразности использования данного подхода в качестве эффективного инструмента для построения гибридных прогнозных систем в спортивной аналитике.

Ключевые слова: сравнительный анализ, прогнозирование результатов, футбол, элементарный образ полинома Колмогорова-Габора, машинное обучение, спортивная аналитика, градиентный бустинг, случайный лес, нейронная сеть, регрессионный анализ

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Introduction

In the field of sports analytics, especially when predicting the outcomes of sports matches, analysts face the challenge of choosing a model that optimally combines accuracy, computational efficiency, and interpretability (Bunker R, Susnyak, 2022; Horvat, 2020). The high degree of stochasticity of this process, due to the influence of numerous factors, requires methods to be able to capture complex nonlinear dependencies in the data (Choi et al., 2023; Yeung et al., 2023). Traditional statistical approaches, such as linear or logistic regression, are often not flexible enough to describe such relationships (Andrianova et al.,2020; Afanasyev, 2020). In turn, modern machine learning methods, including ensemble algorithms (random forest, gradient boosting) and deep neural networks, demonstrate high approximation ability, but may have a number of disadvantages: high resource intensity, a tendency to overfitting on small samples and low interpretability, which limits their analytical value (Balasanyan, Gevorgyan, 2016; Avakyants, Urubkin, 2017; Vladimirova, 2004)

An elementary image of the Kolmogorov-Gabor polynomial can serve as a promising compromise (Svetunkov, 2024). This approach, while preserving its polynomial nature, significantly reduces the "curse of dimensionality" characteristic of a complete polynomial by a two-step transformation: linear convolution of input features followed by a nonlinear polynomial transformation of the result (Ivakhnenko, 1971; Zjavka, Snбљel, 2016). This makes it possible to effectively model nonlinear dependencies, while maintaining a relatively simple procedure for estimating coefficients. the least squares method. As a result, the model has increased interpretability and stability based on limited amounts of data typical for analyzing sports seasons compared to neural network architectures (Svetunkov, Chernyagin, 2024).

The relevance of the study is determined by the growing need for a methodology that allows not only to obtain accurate forecasts, but also to identify key factors affecting performance. Forecasting betting processes is of great practical importance for bookmakers and gamblers, as it allows them to assess the probability of an event outcome and make decisions about participating in betting (Isanberdin, 2022). At the same time, modeling betting processes is a difficult task, since such processes have nonlinear dynamics and non-stationarity. The scientific novelty consists in adapting and applying the elementary image of the Kolmogorov-Gabor polynomial to the task of predicting the results of football matches; in conducting a comparative analysis of the effectiveness of the elementary image of the KGp with basic (linear regression) and modern machine learning methods (gradient boosting, random forest, neural networks) on a single set of data and metrics; in evaluating the elementary the image of the KGp in terms of the balance between prediction accuracy, learning rate, and the potential for interpreting the resulting dependencies (Marateb et al., 2023; Yeung et al., 2023).

The aim of this article is to compare the accuracy and effectiveness of various machine learning methods, including the elementary image of the Kolmogorov-Gabor polynomial, for predicting quantitative (total number of goals in a match) (Belov, Chistyakova, 2008). To achieve the goal, the following tasks are being solved: a) collection and preprocessing of a set of historical data; b) implementation of a model based on an elementary image of the KGp and training and validation of alternative models; c) comparative analysis of results based on a set of metrics (MAE, RMSE, accuracy) and visualizations.

Materials and Methods

Historical data from Zenit football club matches from open sources was used to build and compare models. The target variable y was the number of goals scored by the team in a particular match (an integer value from 0 to 8). Eight indicators characterizing the match and the opponent were used as independent variables (signs):

x_1: match status (1 – home, 0 – away);

x_2: the average number of goals conceded by the opponent at home and away during the season;

x_3: the opponent's position in in the standings;

x_4: the number of goals scored by the opponent in previous matches;

x_5: the percentage of possession of the opposing team;

x_6: the average number of shots allowed by the opponent on his own goal per match;

x_7: the percentage of matches in which the opponent did not concede goals (percentage of "dry" matches);

x_8: the average number of goals scored by the opponent in the matches of the season;

x_9: the average number of expected goals that the opponent can concede in the match (xGA).

All features were standardized before being used in polynomial and linear models:

$$x_i' = \frac{x_i - \mu_i}{\sigma_i}$$

Where μ_i and σ_i – the mean and standard deviation of the sample.

As part of a comparative analysis of machine learning methods for predicting sports events, five different machine learning algorithms were implemented and evaluated: an elementary image of a polynomial, linear regression with regularization, a random forest, gradient boosting, and a neural network.

The Kolmogorov-Gabor polynomial (KGp) is a functional series designed to approximate complex nonlinear dependencies between multiple input variable $x_1, x_2, ..., x_m$ and the output variable y. It has the following form for m=3 (number of factors) (Svetunkov, 2024):

$$y = a_0 + \sum_{i=1}^{3} a_i x_i + \sum_{i=1}^{3}\sum_{j=i}^{3} a_{ij} x_i x_j + \sum_{i=1}^{3}\sum_{j=i}^{3}\sum_{k=j}^{3} a_{ijk} x_i x_j x_k + ...$$

The main disadvantage of the full KGp is the exponential growth in the number of terms with an increase in the number of factors m, which leads to the problem of the "curse of dimensionality" and increases the risk of overfitting. To overcome these limitations, the paper uses an elementary image of the Kolmogorov-Gabor polynomial, a simplified two-stage model:

1. Linear convolution signs:

$$\hat{y}' = b_0 + b_1 x_1 + b_2 x_2 + ... + b_m x_m$$

2. Polynomial convolution transform:

$$\hat{y} = c_0 + c_1 \hat{y}' + c_2 (\hat{y}')^2 + ... + c_k (\hat{y}')^k$$

where k – the degree of the polynomial (usually k $\leq$ 4).

The coefficients are b_i and c_i estimated using the ordinary least squares (OLS) method. This approach retains the ability to approximate nonlinear dependencies with a significantly smaller number of estimated parameters.

The practical implementation of the elementary image of the KGp in the work was carried out through an equivalent construction based on second-order polynomial features:

– the original features were scaled using StandardScaler;

– the transformation into a second-order polynomial space (including all squares and pairwise products of features) was performed;

– ridge regression with L2 regularization was used to estimate the coefficients (Izonin et al., 2024; Selvaraj et al., 2016):

$$\hat{y} = X_{poly}\beta \text{, where } \beta = \arg\min_{\beta} \left\| y - X_{poly}\beta \right\|^2 + \alpha \left\| \beta \right\|^2$$

where X_{poly} is the matrix of extended polynomial features, and α = 1.0 is the regularization coefficient.

The final predictions were rounded to integers and limited to the range [0, 8] corresponding to the realistic number of goals in a football match.

To conduct a comparative analysis, in addition to the elementary image of the KGp, the following algorithms were implemented:

1. Linear regression is a classic statistical method which serves as a baseline for estimating the minimum achievable accuracy using linear methods.

2. Random Forest is an ensemble method based on bagging, which builds a set of decision trees on various subsamples of data and features, then aggregates them predictions by averaging. The algorithm effectively captures nonlinear dependencies and interactions between features,

and is resistant to overfitting and outliers.

3. Gradient Boosting is a modern ensemble method that consistently builds decision trees, each of which learns from the mistakes of the previous ones. Gradient boosting refers to state-of-the-art approaches for tabular data and often shows the best results in regression tasks. The implementation was used in the work GradientBoostingRegressor with 100 trees, a maximum depth of 3 and a learning rate of 0.1.

4. Fully connected Neural Network (Neural Network) is a deep learning model with one hidden layer of 128 neurons with a ReLU activation function. The training was conducted over 30 epochs using the Adam optimizer and the MSE loss function. Neural networks have a high approximation capability (the universal approximation theorem), but require more computational resources and are more difficult to interpret compared to other methods (Svetunkov, 2024).

For the assessment and comparison of models the following metrics were used:

1. Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, n is the number of observations. MAE measures the average magnitude of the forecast error in natural units (goals).

2. Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

RMSE is more sensitive to large forecast errors, which is important when assessing risks in forecasts.

3. Accuracy:

$$Accuracy = \frac{Number\ of\ exact\ matches}{Total\ number\ of\ predictions} * 100\%$$

4. Accuracy ± 1 goal is the percentage of matches in which the discrepancy between the forecast and the fact did not exceed one goal. This metric is important for assessing the practical applicability of models in conditions of high stochasticity of football matches, where accurate prediction of a specific score It is an extremely difficult task.

Results and Discussions

As part of the study, five machine learning models were built and tested to predict the number of goals scored by Zenit Football club in the last 10 matches of the 2022-2023 season. To assess the quality of forecasts, the metrics of average absolute error (MAE), RMS error (RMSE), the proportion of exact matches and the proportion of matches with a deviation of no more than one goal were used. The results of the comparative analysis are presented in Table 1.

Table 1. Comparison of forecast accuracy of different models.

Model	MAE	RMSE	Accuracy	Accuracy ± 1 goal
Elementary image of the KGp	1.5	1.97	30%	50%
Linear Regression	1.5	1.92	30%	50%
Random Forest	1.2	1.61	20%	80%
Gradient boosting	1.3	1.76	30%	60%
Neural network model	1.1	1.3	20%	70%

In a comparative analysis of five Zenit performance forecasting models based on the metrics MAE, RMSE, accuracy and accuracy ± 1 goal, the neural network showed the best result for MAE (1.1) and RMSE (1.30), which indicates the minimum average deviation of forecasts. However, in terms of practical applicability (±1 goal), a random forest leads with a score of 80%, while the neural network demonstrates 70%, and the elementary image of the Kolmogorov-Gabor polynomial and linear regression are 50% each. At the same time, according to the accuracy of the exact matches of the KGp, the linear regression and gradient boosting showed a maximum of 30%, while more complex models showed 20%. Thus, for tasks where the minimum average error is critical, a neural network is optimal; for the maximum practical usefulness of forecasting, a random forest; and for analytical tasks requiring interpretability of the contribution of features, the elementary image KGp, which, without yielding in accuracy, ensures the transparency of the model by analyzing the coefficients of the polynomial.

Figure 1 shows the predicted values of the model based on the elementary image of the Kolmogorov–Gabor polynomial compared to the actual results. Figures 2,3,4,5 illustrate the results for the linear regression, random forest, gradient boosting and neural network models, respectively. A summary comparison of the three models is presented in Figure 6.

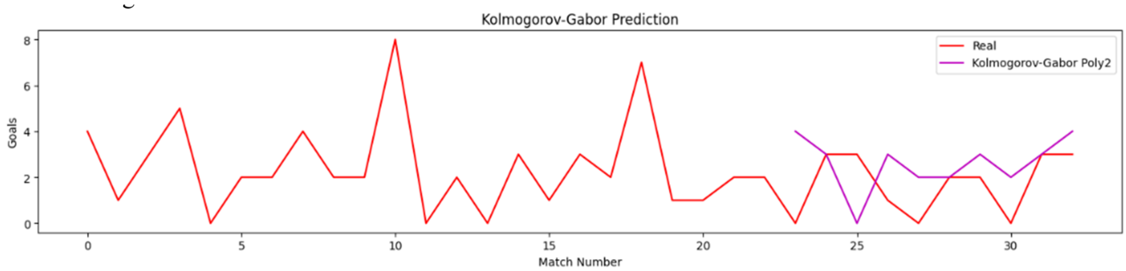

Fig. 1. Graph of the forecast of the number of goals scored by the Zenit team for 10 matches using a model based on the elementary image of the Kolmogorov–Gabor polynomial.

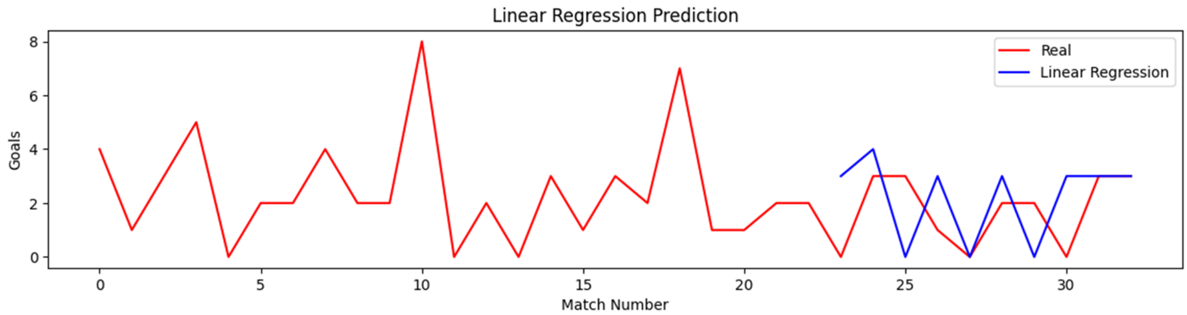

Fig. 2. Graph of the forecast of the number of goals scored by the Zenit team for 10 matches using a model based on the linear regression.

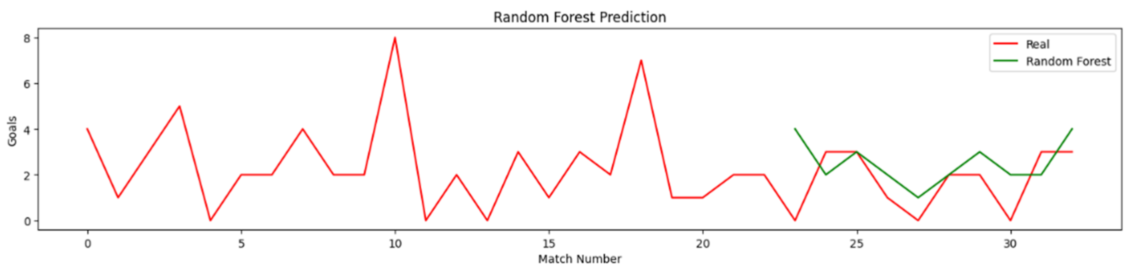

Fig. 3. Graph of the forecast of the number of goals scored by the Zenit team for 10 matches using the random forest model.

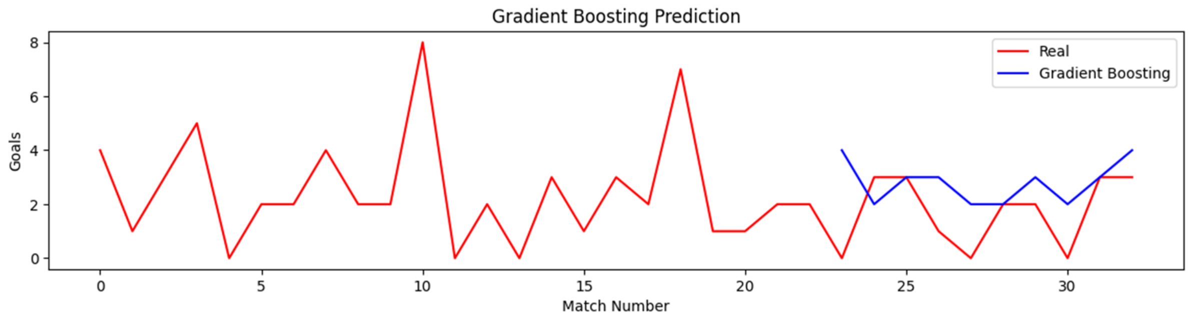

Fig. 4. Graph of the forecast of the number of goals scored by the Zenit team for 10 matches using a model based on the gradient boosting.

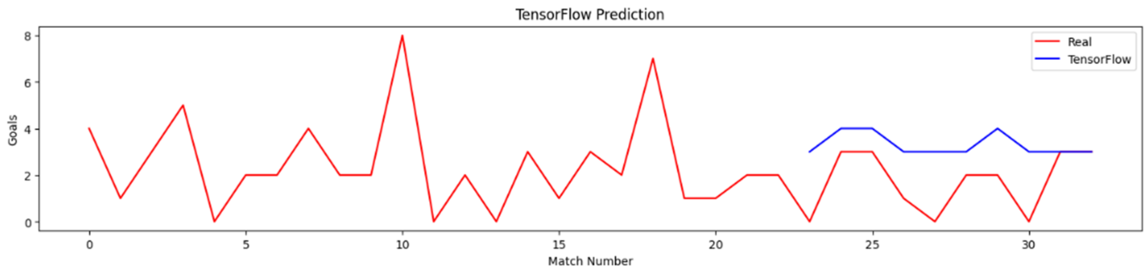

Fig. 5. Graph of the forecast of the number of goals scored by the Zenit team for 10 matches based on a neural network model.

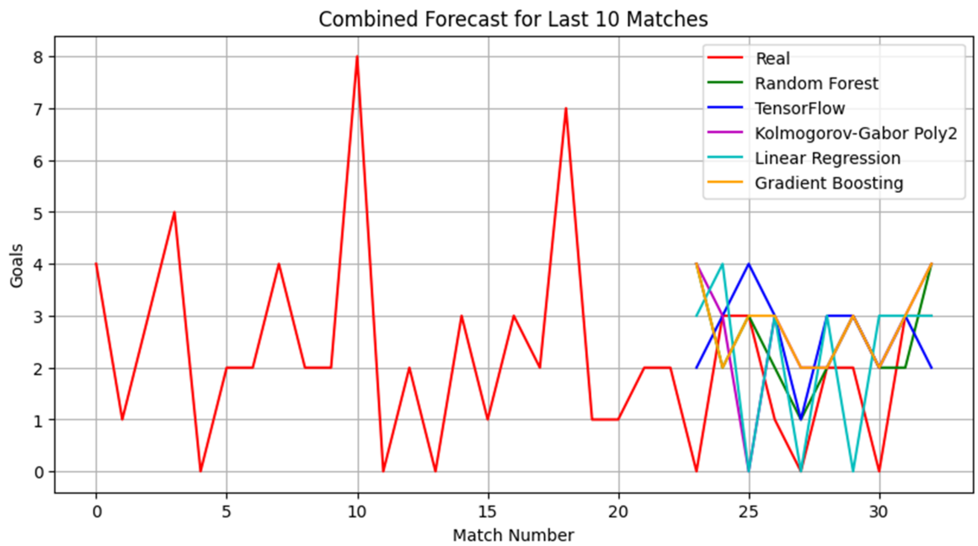

Fig. 6. Comparison of model forecasts with actual values of the number of goals scored by the Zenit team.

To demonstrate the key advantage of the model - its interpretability - an analysis of the most significant features in the polynomial model was carried out. Since the elementary image of the Kolmogorov-Gabor polynomial is implemented through second-order polynomial features, we can analyze the coefficients of the resulting model. Figure 7 shows the top 10 most significant terms of the polynomial.

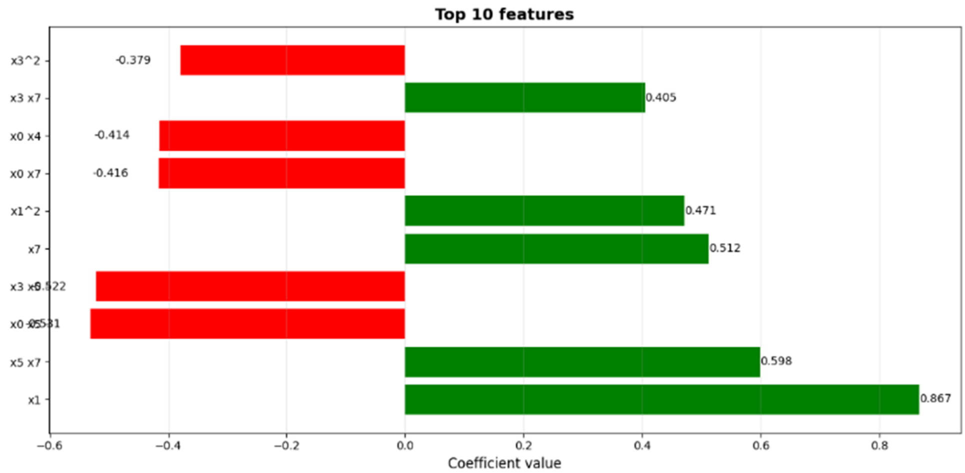

Fig. 7. Top 10 most significant terms of the polynomial.

The analysis of the significance of the coefficients of the polynomial model revealed the key performance factors of FC Zenit. The most significant individual factor turned out to be the status of the match: playing at home significantly increases the likelihood of more goals scored (Bussgang et al., 1974). The second most powerful limiting factor was the defensive reliability of the opponent, measured by the percentage of "dry" matches. At the same time, the greatest complex threat to Zenit's attack is created by teams combining high ball possession with organized defense - their interaction in the model showed the maximum negative effect after the home factor. Non-linear effects, such as the square of home status, and interactions, such as the opponent's position with his defensive discipline, also have a significant impact. These results emphasize that for an accurate forecast, it is necessary to take into account not only the individual indicators of the opponent, but also their impact depending on the conditions of the match (Enikeeva, 1992).

Conclusion

As part of the research, the main goal was successfully achieved - a comparative analysis of the accuracy and effectiveness of various machine learning methods for the task of quantifying the performance of football matches was carried out. Special attention was paid to assessing the prospects of using the elementary image of the Kolmogorov-Gabor polynomial in the context of sports analytics (Luparev, Svetunkov, 2025). To achieve this goal, all tasks have been consistently solved: the collection and preprocessing of a set of historical match data has been carried out; and a forecasting model based on the elementary image of the KGp has been implemented; in parallel, they have been trained alternative models: linear regression, random forest, gradient boosting, neural networks); a comparative analysis of their work was carried out based on a comprehensive set of metrics (MAE, RMSE, accuracy, accuracy ± 1 goal) using visualization methods. The results obtained allow us to state that the model based on the elementary image of the Kolmogorov-Gabor polynomial has demonstrated a quite competitive level. accuracy. The indicator of 30% accurate matches of the actual and predicted values of the number of heads is not inferior to the results shown by such modern and powerful methods as gradient boosting, and even surpasses the random forest and neural network model in this parameter. This is a significant result, given the relative simplicity and computational efficiency of the polynomial model compared to more complex algorithms (Enikeeva, 1992; Vereshchagin, 2013; Chernyagin, 2024)

At the same time, as expected, the key advantage of the complementary image of the KGp over the alternatives remains its full interpretability and explainability. Unlike "black box" models (neural networks, ensembles of trees), the structure of the polynomial allows not only to make a forecast, but also to conduct a deep analytical analysis of the factors that determine it. The researcher gets the opportunity to quantify the contribution of each initial feature (match status, opponent statistics, etc.), as well as analyze the strength and nature of nonlinear interactions between them. This It transforms the model from a simple forecasting tool into a powerful analytical research tool capable of generating meaningful hypotheses about the nature of athletic performance. Of course, by metrics such as the average absolute error (MAE=1.5) and the standard deviation (RMSE=1.97), the polynomial model is inferior to the best of the considered algorithms. However, this gap in accuracy can be considered an acceptable price to pay for the acquired quality - transparency and controllability of the forecasting process. In applied conditions, especially in the expert environment of coaches, analysts, and managers of sports clubs, the ability to understand and argue the reasons for a forecast is often valued no less, and sometimes more, than its extreme accuracy.

Thus, the results confirm the main hypothesis of the study: the elementary image of the Kolmogorov-Gabor polynomial represents an effective methodological compromise. It offers a balance between predictive power sufficient for practical use and a degree of explainability. This makes it a valuable tool not only in the arsenal. a data science specialist who solves the problem of forecasting, but also in the hands of a sports analyst who strives for an in-depth, causal understanding of the factors influencing the success of a team. The prospects for further development of the method are seen in the study of higher-order polynomials, the combination of elementary KGp with other algorithms within the framework of ensemble approaches, as well as in the adaptation of the methodology to other classes of predictive tasks in sports analytics (Iliyasu et al., 2023).

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