IRSTI 28.23.37 https://doi.org/10.26577/jpcsit2024020102

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FLOOD FORECASTING IN MALAYA ALMATINKA RIVER VIA MACHINE LEARNING AND DEEP LEARNING WITH OVERSAMPLING

Abstract. Flooding, a phenomenon characterized by the overflow of water from its natural confines onto dry land, poses significant threats to communities and infrastructure, often resulting from heavy precipitation, snow melting, and various natural and anthropogenic factors. The causes of flooding encompass a myriad of influences, including intense rainfall, precipitation patterns, and meltwater accumulation. Such events precipitate abrupt rises in river and lake levels, accompanied by the formation of barriers. The breaching of dams and levees can trigger the rapid propagation of large volumes of water, generating formidable breach waves.

In contemporary flood management practices, machine learning and deep learning algorithms have emerged as indispensable tools for forecasting and mitigating flood risks. This study focuses on predicting floods in the Malaya Almatinka River, situated in Almaty, Kazakhstan. Leveraging a diverse set of algorithms including XGBoost, LightGBM, RandomForest, SVM, Linear Regression, and neural networks, the research endeavors to enhance flood prediction accuracy. However, during the data preprocessing phase, it was observed that the dataset suffered from imbalance, necessitating the implementation of Random Over-Sampling to rectify the issue and ensure more equitable representation across classes. Through the fusion of advanced computational techniques and empirical data, this research aims to contribute towards more effective flood forecasting strategies, thereby bolstering the resilience of communities in flood-prone regions.

Key words: Malaya Almaty, floods, machine learning, deep learning, Over-Sampling, Random Over-Sampling, XGBoost, LightGBM, RandomForest, SVM, Linear Regression, neural network.

1 Introduction

Flooding is one of the most destructive natural disasters occurring worldwide. Recurrent disasters require solution methods using information technologies such as machine learning and deep learning. The climate of the city of Almaty, where the Malaya Almatinka River is located, is rainy and the average amount of precipitation is 600-650 mm per year [1]. A lot of scientific papers are devoted to topics such as predicting flooding, for determining an area as having very low to very high flood potential, through approaches that use hydrological-hydraulic models for flood modeling. And there are also works dedicated to the study of flood susceptibility through geospatial technologies [2-11] and a lot of references to these are given in the work [12]. Although strong and non-persistent rains have been noted as one of the main causes of flooding in several places, flooding observed in various regions of Almaty was the result of sudden reservoir openings, indicating poor dam management. Floods in the Malaya Almatinka River are caused by several factors including unexpected water flows, meltwater from surrounding mountain tops, and ice jams. Ice jams are irregular, transitory events that vary greatly based on hydrological, hydraulic and ice conditions along the river. The chaotic nature of river ice jam formation makes predicting water levels resulting from ice jams a more complex task than predicting open water floods. Small changes in ice dam water discharge, ice jam formation sites, and initial water levels during an ice jam can result in various bridge support damage. The water depths can significantly exceed the open water depths for the equivalent flow. This means that small flows can cause extremely dangerous flood water levels during spring ice dam breakup, making forecasting and warning about ice jam flooding hazards especially important. Jupyter Notebook was used as the environment and Python was the language of execution. The machine learning algorithms can quickly provide results and be used for predicting floods.

2 Research Domain

The study area considered was the Malaya Almatinka. The Malaya Almatinka is a river in the city of Almaty, a right tributary of the river Kaskelen. It originates from the Tuyuksu glaciers of the Zailiysky Alatau ridge. It is 125 km long and has a drainage area of 710 km². The main tributaries are Sarysai (Yellow Log), Kuygensai (Gorelnik), Kimasar (Komissarovka), Zharbulaq (Kazachka), Batareika (Bedelybay), Butakovka, Karasu-Turksib, Esetai, Karasu, and Terenkara [13].

In 1889, a strong rainstorm caused a landslide that swept away several streets in Verny, a district in the province. Newspaper chronicles of those times meticulously reported on the number of casualties and the scale of the tragedy: "Lost, destroyed...". In 1921, a catastrophic flood occurred. On the night of July 8th to 9th, an unprecedented flood swept through the entire Semirechensk region in the mountainous part of the region due to the delayed spring floods that had been held up for nearly two months. A mass of winter snow covered the mountains, but several hot days and nights, accompanied by dry mist from the sandy deserts of Kyzylkum and Karakum and hot wind "garisel," caused rapid destruction of the snow. When the snow was finally washed away by the rain, it fell in a short period of time as a whole mass into the river beds and of course, flooded them beyond all limits. In 1921, the water rise in the Malaya Almatinka River in Almaty began on July 8th and reached 5-6 sazhen (about 10 meters) by midnight. The flow threw debris from houses and large boulders into the city, heading towards the Narinskaya (now Valikhanov) and Kapal'skaya (now Kunayev) streets. That night, 65 residential houses were destroyed, 82 were damaged, 177 farm buildings were destroyed, 63 were damaged, and 18 mills were destroyed and damaged. One beekeeping was taken from 57th street, one tobacco factory was destroyed, and two leather factories were damaged. 140 bodies (63 of them children) have been found, around 500 people are missing, 80 were injured and around 1500 families were affected, or 7% of the total population of Almaty. There have been three major floods in the Malaya Almatinka River in the last 80 years, the first in 1956, the second in 1966 (which was prevented), and the third in July 15, 1973, when a dam was destroyed in the Mynzhylky settlement. Over 70 people died in the 1973 flood. The Malaya Almatinka River regularly overflows its banks every year.

3 Research procedure

The research procedure consists of the following stages: data collection, data set processing and balancing, training machine learning and deep learning algorithms.

3.1 Data Collection

The data for predicting floods was selected according to the recommendations of the World Meteorological Organization. According to their recommendations, the data should contain information on precipitation, temperature, elevation, slope, etc. [14]. The dataset consists of 12 attributes, of which 11 are factors affecting floods and one column is the target (target) variable, which takes a value of 0 if there was no flood and 1 if there was a flood. The attributes:

- Maximum temperature
- Minimum temperature
- Average temperature
- Wind type and direction
- Slope
- Region type
- Region date
- Height above sea level
- Precipitation amount
- Wind speed

The dataset consists of 2059 data points. The region attribute includes 6 unique values: Almaty, Medeu, Esik, MPK, Airport, Kamenskoe Plateau. The temperature attributes contain the average monthly temperature, and the precipitation attribute contains data on monthly precipitation. The "wind direction and type" column contains data on wind direction and type, as well as wind speed. The slope column contains data on the slope of the area, with the value of this attribute specified in degrees. The region type attribute includes data on such region types as mountain, city, and settlement. The height attribute includes data on the height of the region above sea level.

The target value data has two values, such as 1 and 0. 1 indicates that there was a flood, and 0 indicates that there was no flood. The dataset was collected from 1880 to 2020. The dataset was collected from open sources [15-24].

3.2 Data Processing

During the data processing, methods such as LabelEncoder and StandardScaler were used. The dataset has 3 categorical attributes: "Region", "DD", and "Land_use", and the values of the processed data are shown in Table 1.

Table 1 – Table with values of processed data

Attribute name	Original value	Data after encoding
Region	Almaty Medeu Esik Bao Airport Kamens.p	1 5 3 2 0 4
DD (wind type and direction)	Calm, Calmness Wind blowing from North-Northeast Wind blowing from East-Southeast Windblowing from East Windblowing from North Windblowing from Southwest Windblowing from South Windblowing from South-Southeast Windblowing from Northeast Windblowing from Southeast Windblowing from Northwest Windblowing from South-Southwest Windblowing from West-Southwest Windblowing from East-Northeast Windblowing from West-Northwest Windblowing from West Windblowing from Unspecified direction.	16 10 3 1 7 13 11 14 8 12 9 15 6 2 5 4 0
Land_use	City Mountain Town	0 1 2

3.3 Random Oversampling

The Random Over-Sampling (ROSE) technique was used in the work. The sample collected for training was unbalanced, which would negatively impact the quality of the trained models in the future. Therefore, the Over-Sampling method was used to produce a balanced data sample.

Random Oversampling is based on generating new artificial data from classes according to the approach of a smoothed initial loading [25].

Initially, the method focuses on X domains, which are in R^d, i.e. P(X)=f(X) is the probability density function on X. The method can assume that $n_j < n$ is the size of Y_j, $j = 0,1$without loss of generality. Below is the algorithm for creating one instance:

I. Select $y = Y_j \epsilon Y$ with a probability of 0.5

II. Select $(x_i|y_j)$ in T_n such that $y_j = y$ with a probability of $p_i = \frac{1}{n_i}$

III. The instance x is generated with $K_{Hi}|(*, x_i)$, c K_{Hi}, a probability distribution with center at x_i and H_j is the scaling parameter matrix.

The method selects an observation from the training sample that belongs to one of two classes (chosen by assigning equal probability to Y_0 and Y_1), and creates a new set of data in the surroundings of the selected class, where the width of the surroundings is H_j. Usually, K_{Hj} is selected from the set of unimodal symmetrical distributions. It is worth noting that after class selection, the labels take the form:

$$\hat{f}(y = Y_j) = \sum_{i=1}^{n_j} p_i Pr(x|x_i) = \sum_{i=1}^{n_j} \frac{1}{n_j} Pr\,(x_i) = \sum_{i=1}^{n_j} \frac{1}{n_j} (x - x_i).$$

The implementation of all three steps creates a new training dataset T_m^*, where m is an equal number of instances belonging to two classes. Figure 2 shows the class plots before and after applying the ROSE method.

After the ROSE method, the data was increased to 4010 rows, of which 90% (3609 rows) were set aside for training, and the remaining 10% (401 rows) were intended for model testing.

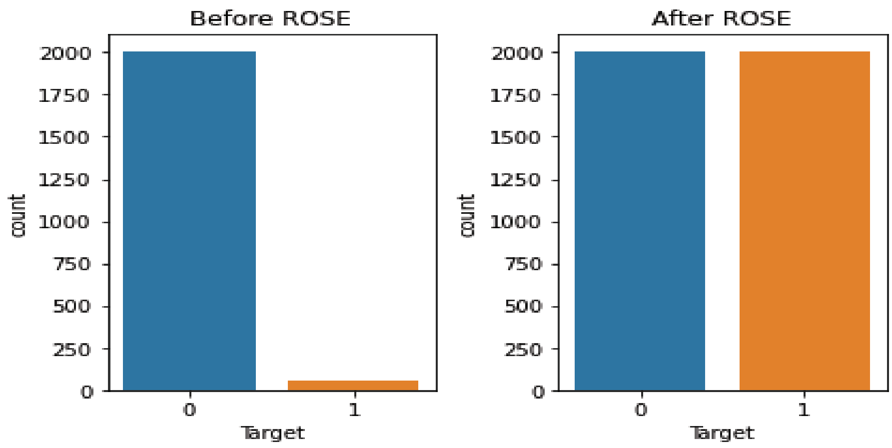

Figure 1 – Plot of Classes Before and After the ROSE Method

4 Flood predictions in the Malaya Almatinka River using machine learning algorithms

4.1 Linear Regression

Linear regression is a statistical model that describes the dependence of one variable on several other variables. It is implemented in the Python programming language in the scikit-learn library. In the study, two models were studied. The first model was trained without the ROSE method, and the second model was trained with the ROSE method. Table 2 presents the weights and results of the models. Figure 2 shows a visual comparison of the prediction results of the models.

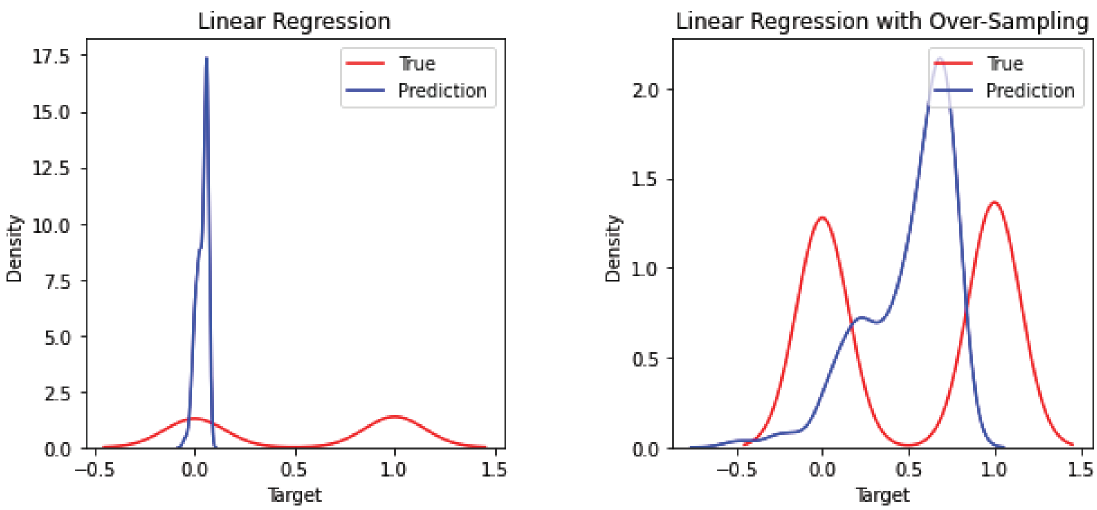

Figure 2 – Results of Linear Regression Models

Based on the metric results, particularly R2, the model trained with the ROSE method shows 7 times better results compared to the model without the use of ROSE.

4.2 Support Vector Machine

According to the paper "Flood Prediction Using Machine Learning, Literature Review" published in 2018 by Amir Mosavi, Pinar Ozturk, and Kwok Wing Chau, the Support Vector Regressor (SVR) algorithm is a very popular and effective algorithm in hydrology and flood prediction. Based on their research, SVR was used in this work [26].

The hyperparameters of two models based on the SVR algorithm are presented below.

– kernel = 'rbf';

– c = 10000.

The training results are presented in Table 2. The graphical comparison of the predictions is shown in figure 3.

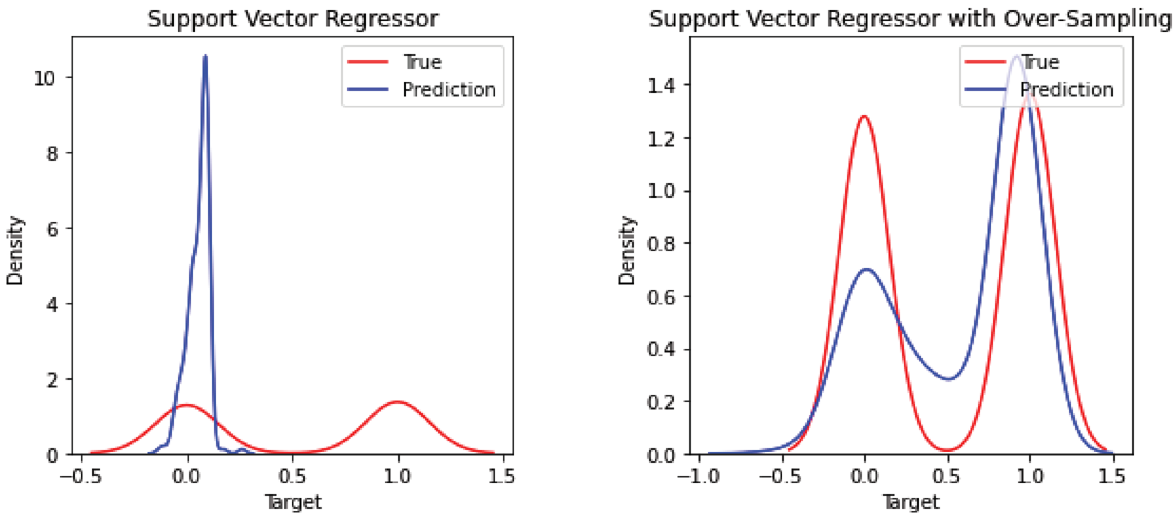

Figure 3 – Graphical Representations of the SVR Model Predictions

4.3 XGBoost Regression

The XGBoost algorithm is a modern, popular machine learning algorithm based on Gradient Boosting Decision Tree. Extreme Gradient Boosting was proposed by Dr. Tianqi Chen from the University of Washington. Unlike other decision tree ensemble methods, XGBoost is known for its fast processing speed due to parallel feature selection, accuracy, and the addition of regularizations to enhance the generalization effect of the model [27].

During the work, default hyperparameters were selected for training two models, except for random_state, whose value is 42. Random_state was set for repeatability of results. Table 2 shows the results of the trained model, and figure 4 shows the prediction graph of two models.

4.4 Random Forest

Random Forest Regressor is an ensemble-based machine learning algorithm that uses decision trees. It's well-regarded for its simplicity and speed in implementation. The algorithm works by building multiple decision trees and producing answers through voting (majority).

During the work, the following hyperparameters were selected:

- n_estimators=10;
- criterion='mae';
- min_samples_split=2;
- random_state=42.

Table 2 shows the results of the Random Forest model training and Figure 5 shows the prediction graph of the Random Forest models.

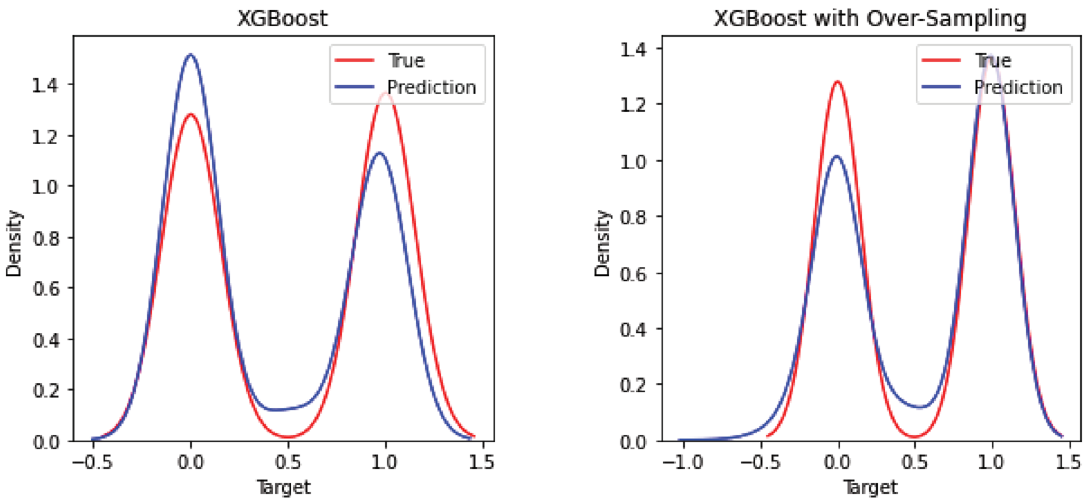

Figure 4 – Graphical Representation of XGBoost Model Predictions

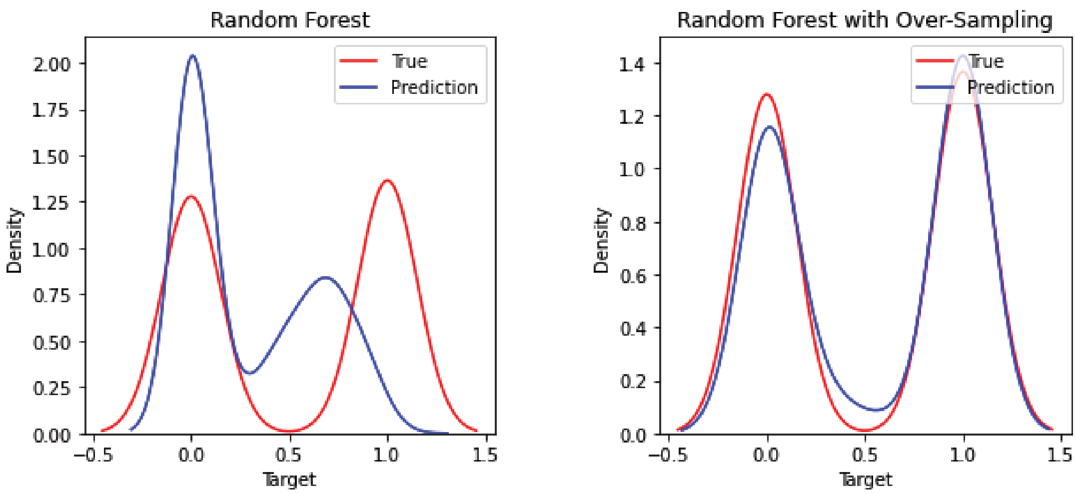

Figure 5 – Visual representation of predictions made by Random Forest models

4.5 LightGBM

Light Gradient Boosting Machine – machine learning method based on XGBoost. The algorithm was created in 2017 by Microsoft [28]. Since LightGBM is based on Boost, it has the same methods as parallel arithmetic, except LightGBM learns faster and uses less memory. The most important difference from XGBoost is the use of a tree-by-leaf growth algorithm. The leafwise method can converge faster than the growth in depth. But the main disadvantage of the method is that hyperparameters need to be adjusted for algorithm optimizations [29].

The following hyperparameters were modified to create the model:

- bagging_fraction=0.7;
- bagging_freq=10;
- feature_fraction=0.9;
- learning_rate=0.005;
- max_bin=512;
- max_depth=None;
- metric=[‘l2’, ‘auc’];
- n_estimators=10;
- num_iterations=100000;
- num_leaves=128;
- objective=’regression’;
- random_state=42;
- task=’train’;
- verbose=0.

The results of the metrics are shown in Table 2 and Figure 6.

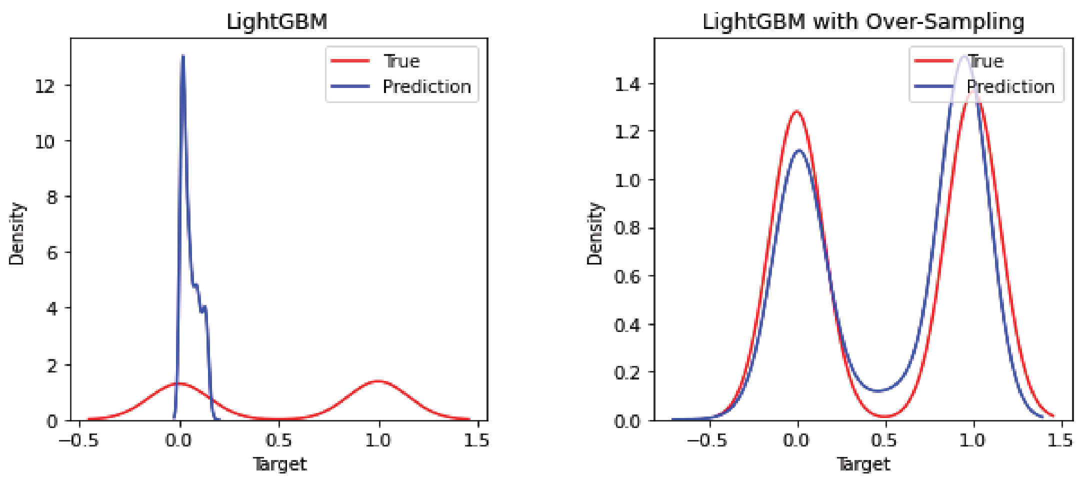

Figure 6 – LightGBM model prediction graphics

5 Flood predictions in the Malaya Almatinka River using deep learning algorithms

5.1 Neural Network

A neural network is a mathematical model or software and hardware implementation based on the principle of biological neural networks [30].

A neural network was built for predicting floods in Almaty. The neural network consists of 9 layers, with 1 input layer, 1 output layer, and 8 hidden layers. The following activation functions were used in the neural network: ReLU, ELU, LeakyReLU, Sigmoid. To prevent overfitting, the dropout and Early Stopping methods were used, where Early Stopping was triggered when the value of the MSE loss function was less than 0.02. The Adam optimizer was chosen as the optimization of weights. In total, 1500 epochs were used for training with a batch size of 32.

Weight initialization. In all the layers of the neural network, the weights were initialized by default, i.e. with the GlorotUniform method. GlorotUniform, also known as Xavier initialization, assigns weights from a uniform distribution value.

$$w_i \sim U\left[-\sqrt{\frac{6}{fan\_in + fan\_out}}, \sqrt{\frac{6}{fan\_in + fan\_out}}\right]$$

The fan_in represents the number of input paths to the neuron, while the fan_out represents the number of output paths to the neuron [31]. Additionally, all bias values were set to 0.

The model values were verified by allocating 10% of the training set for validation, which is 361 rows. A more detailed architecture is shown in figures 7, and the training results are shown in figure 8. The results of the metrics are indicated in Table 7.

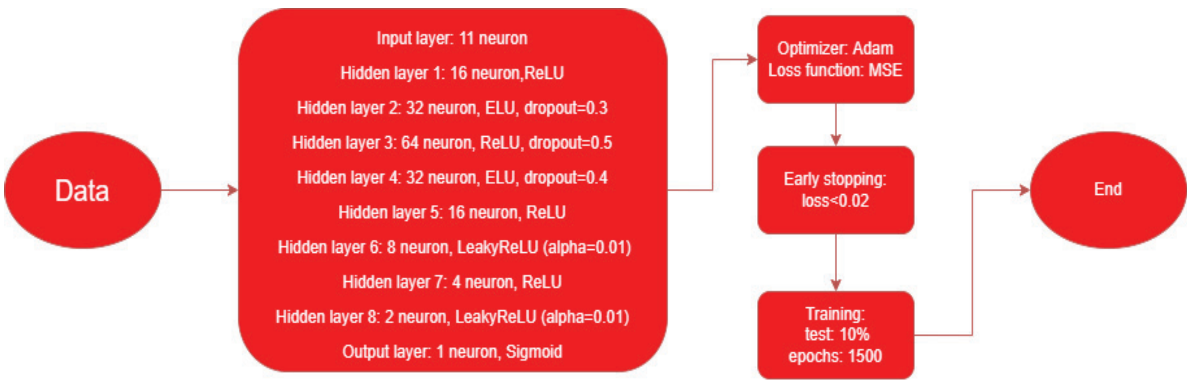

Figure 7 – Neural Network Working Process

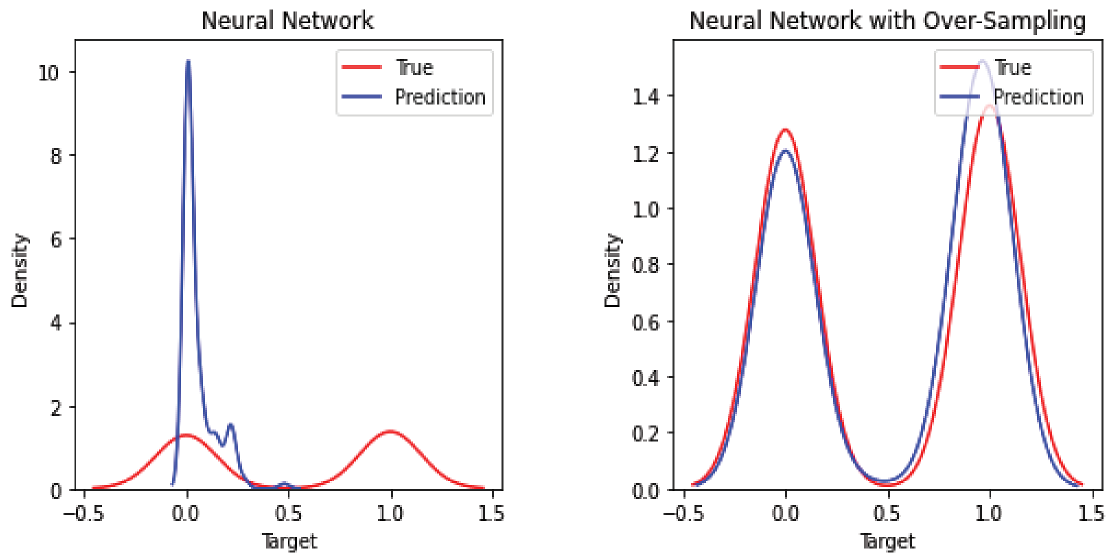

Figure 8 – Graphical representation of the neural network's prediction

6. Results and Discussion

Two models were generated for each algorithm type. Findings from the investigation revealed that, owing to class imbalance within the dataset, models trained without employing the ROSE method exhibited subpar performance across metrics such as MSE, MAE, and R^2. The substantial class imbalance directly contributed to this outcome. As illustrated in Table 2, models trained using the ROSE method demonstrated a notable improvement, averaging 5-8 times better performance compared to their counterparts. Similarly, Table 2 highlights the superiority of models trained with the ROSE method in terms of MAE metric. Moreover, these models consistently outperformed others in the determination coefficient metric, as evidenced in Table 2.

Table 2 – The metric's results of algorithms

Quality metrics of the algorithms	MSE	MSE (ROSE)	MAE	MAE (ROSE)	R^2	R^2 (ROSE)
Linear Regression	0.46585	0.1938	0.5044	0.3932	-0.8653	0.2238
Support Vector Machine	0.4157	0.0967	0.4888	0.1972	-0.6658	0.6126
XGBoost	0.0753	0.012	0.0994	0. 0533	0.6984	0.9241
Random Forest	0.138	0.0122	0.2331	0.297	0.4474	0.951
LightGBM	0.4327	0.0264	0.4847	0.0781	-0.7324	0.8944
Neural Networks	0.4296	0.0391	0.4779	0.06	-0.7202	0.8434

7. Conclusion

In this research, machine learning algorithms and neural networks trained using the ROSE method were employed to forecast river flooding in the Malaya Almatinka river. Initially, the research utilized ROSE to rectify the imbalanced dataset issue by generating synthetic classes. Two models were trained for comparative analysis, one incorporating OverSampling and the other without.

The occurrence of a flash flood phenomenon is contingent upon several factors, including the nature of the dataset used for training predictive models. In this context, the presence or absence of flash floods becomes a nuanced consideration due to the artificial augmentation of training data using the ROSE algorithm. The Malaya Almatinka River has encountered scarce instances of flash floods historically, thus making the training dataset inherently deficient in such events.

However, the study undertook a comprehensive approach by constructing predictive models using both authentic historical data and ROSE-generated datasets. This methodological diversification allowed for a comparative evaluation of model performance under varying training conditions.

Upon analysis, the results revealed a discernible disparity in accuracy metrics. Models trained on authentic historical data exhibited accuracy rates ranging from 45% to 70%, reflecting the inherent challenges posed by the limited occurrence of flash floods in the dataset. In contrast, models trained on ROSE-augmented data showcased significantly higher accuracy rates, ranging from 92% to 95%. This disparity underscores the efficacy of the ROSE algorithm in synthesizing data conducive to the identification and prediction of flash flood events. Moreover, it highlights the importance of employing advanced computational techniques in mitigating the limitations imposed by sparse historical datasets, thereby enhancing the robustness and reliability of predictive models in flood risk assessment and management.

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Submission received: 24 March, 2024.
Revised: 24 March, 2024.
Accepted: 24 March, 2024.