**International Journal of Electrical and Computer Engineering (IJECE)**
Vol. 14, No. 2, April 2024, pp. 1842~1850
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i2.pp1842-1850


# Predicting and detecting fires on multispectral images using machine learning methods

**Murat Aitimov[1], Mira Kaldarova[2], Akmaral Kassymova[3], Kaiyrbek Makulov[4], Raikhan Muratkhan[5], Serik Nurakynov[6], Nurmakhambet Sydyk[6], Ideyat Bapiyev[3]**

[1]Kyzylorda Regional Branch at the Academy of Public Administration under the President of the Republic of Kazakhstan, Kyzylorda, Republic of Kazakhstan
[2]Department of Information Systems, S. Seifullin Kazakh Research Agrotechnical University, Astana, Republic of Kazakhstan
[3]Department of Information Technology, Faculty of Technology, Zhangir Khan University, Uralsk, Republic of Kazakhstan
[4]Department of Computer Science, Faculty of Science and Technology, Caspian University of Technology and Engineering Named after Sh. Yessenov, Aktau, Republic of Kazakhstan
[5]Department of Applied mathematics and Informatica of Karaganda Buketov University, Karaganda, Republic of Kazakhstan
[6]Institute of Ionosphere, Almaty, Republic of Kazakhstan

**Article Info**

***Article history:***

Received Aug 27, 2023
Revised Oct 24, 2023
Accepted Nov 29, 2023

***Keywords:***

Extreme gradient boosting
Fire
Logistic regression
Machine learning
Multispectral images
Vanilla convolutional neural network

**ABSTRACT**

In today's world, fire forecasting and early detection play a critical role in preventing disasters and minimizing damage to the environment and human settlements. The main goal of the study is the development and testing of machine learning algorithms for automated detection of the initial stages of fires based on the analysis of multispectral images. Within the framework of this study, the capabilities of three popular machine learning methods: extreme gradient boosting, logistic regression, and vanilla convolutional neural network (vanilla CNN), are considered in the task of processing and interpreting multispectral images to predict and detect fires. XGBoost, as a gradient-boosted decision tree algorithm, provides high processing speed and accuracy, logistic regression stands out for its simplicity and interpretability, while vanilla CNN uses the power of deep learning to analyze spatial and spectral data. The results of the study show that the integration of these methods into monitoring systems can significantly improve the efficiency of early fire detection, as well as help in predicting potential fires.

*This is an open access article under the CC BY-SA license.*

***Corresponding Author:***

Ideyat Bapiyev
Department of Information Technology, Faculty of Technology, Zhangir Khan University
090000 Uralsk, Republic of Kazakhstan
Email: bapiev@mail.ru

## 1. INTRODUCTION

Forest fires are one of the most destructive natural phenomena, causing significant damage to ecosystems, economies, and human well-being. In light of global climate change and increasing human impacts, the need for rapid and accurate fire prediction and detection has become increasingly urgent. The main challenge here is the need for effective fire prediction and detection in multispectral images. To solve this problem, it is proposed to develop and optimize highly efficient machine learning models capable of analyzing multispectral images to accurately predict and detect fires. These models must be trained on large amounts of data, including a variety of scenarios and types of multispectral data, to ensure their broad applicability. Traditional methods of detection and control often do not provide the necessary effectiveness, so the focus is on innovative approaches. In recent decades, the development of Earth remote sensing technologies has made it possible to obtain high-resolution multispectral images. These images [1]–[3]

provide extensive information about the condition of the surface, including temperature, humidity, and other parameters that can serve as indicators of fire hazard. However, processing and analyzing such a volume of data requires the use of modern and effective tools. In this context, machine learning techniques such as extreme gradient boosting [4]–[6], logistic regression [7]–[9], and vanilla convolutional neural networks (vanilla CNN) [10]–[12] are emerging as promising tools that offer advanced solutions for wildfire management: prediction and early detection based on multispectral image analysis. The purpose of this study is to comparatively analyze the effectiveness and applicability of these machine learning methods in fire detection tasks. The purpose of the work is not only to determine the optimal methods for solving this problem but also to develop recommendations for their practical application. The importance of this work can hardly be overestimated, given the possible consequences of fires [13] and the need to increase the efficiency of early warning systems [14], [15]. The research results are expected to make significant contributions to the fields of remote sensing, machine learning, and environmental security.

Since 2020, interest in applying machine learning to multispectral image analysis in the field of fire detection has increased significantly. This is due to the increase in forest fires around the world and the need for improved monitoring methods. Recent research has focused on deep learning, especially convolutional neural networks (CNNs), for multispectral image processing [16]. XGBoost, a gradient-boosting algorithm, has been applied to fire detection based on the analysis of image characteristics and their time series [17]. Works such as the study by Rashkovetsky *et al.* [18] demonstrated the successful application of deep learning for fire detection using CNN architecture for image classification and segmentation. In addition to analyzing multispectral images, researchers have integrated data from various sources, such as meteorological data, to improve forecast accuracy [19].

## 2. METHODS

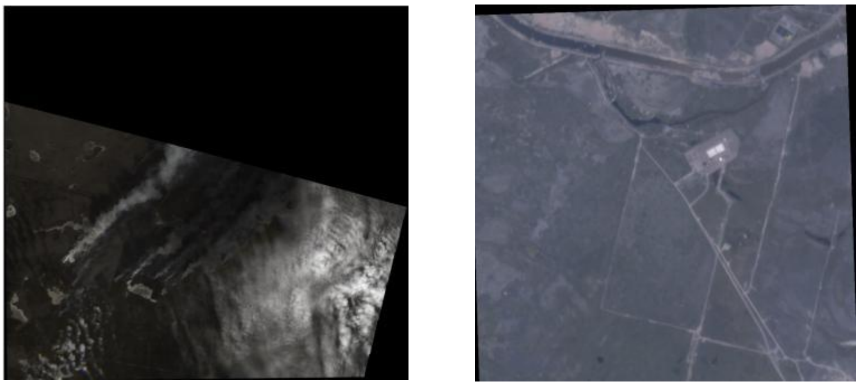
To effectively predict and detect fires on multispectral images, the following machine learning methods were chosen: XGBoost, logistic regression, and vanilla CNN. Before starting to train the models, the data were preprocessed [20], [21], that is, with the vegetation indices normalized difference vegetation index (NDVI) and normalized difference water index (NDWI). By applying both of these indices together, a more detailed picture of the health and moisture content of vegetation in a given area was obtained. If NDVI [22]–[25] decreases (vegetation becomes less healthy or less dense) and NDWI also decreases (vegetation becomes less moist), this may be an early indication of an increased fire risk in the area. It should be noted that fire forecasting requires an integrated approach, and vegetation indices alone may not be enough. They are often used in conjunction with other data and methods such as weather, temperature, humidity, and fire history for more accurate forecasting.

Next, multispectral images are divided into small segments (patches), which are then used to train models. The values of each spectral band are normalized to ensure the same scale and improve the convergence of the algorithms. The data is divided into training, validation, and test sets. XGBoost training uses a gradient-boosting algorithm to build a set of weak models, combining them into one strong model. Optimizing hyperparameters (e.g. learning rate, maximum depth of trees) greatly improves model performance. Next, metrics such as accuracy, recall, and F1-score are used to assess the quality of the model on the validation and test sets.

In the course of our research, we, the authors of this article, trained models using logistic regression and CNN architecture to solve the problem of predicting and detecting fires in multispectral images. We modeled the probability of objects belonging to different classes, such as fire and non-fire, using various metrics such as precision, recall, F1-measure, and receiver operating characteristic curve (ROC curve) to evaluate the performance of the models. For training, an error backpropagation algorithm was used to minimize losses. Additionally, we used a data augmentation method, which improved the generalization ability of the models. In the process of analyzing the classification results, we used the error matrix to visualize the results. After completing the training and evaluation of the three models, we conducted a comparative analysis of their effectiveness on the validation and test sets. Based on the results obtained, we concluded the most suitable method for successfully solving the problem of predicting and detecting fires in multispectral images.

## 3. RESULTS AND DISCUSSION

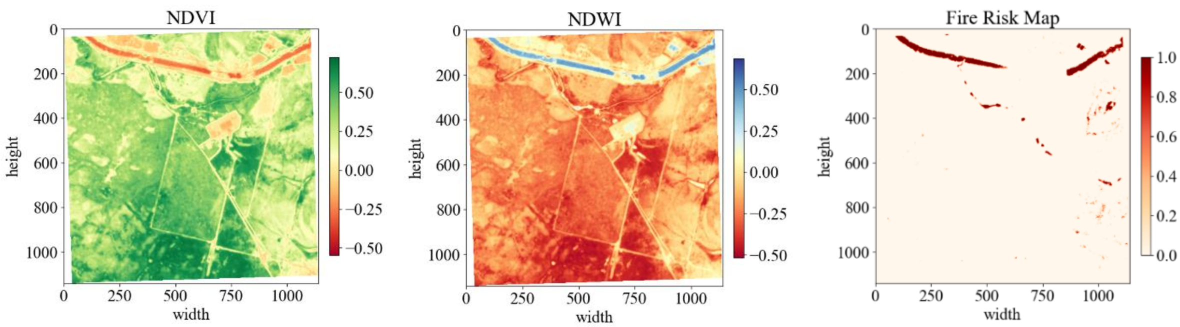
In the field of data processing and machine learning, various approaches and algorithms are used, each of which has its characteristics, advantages, and disadvantages. XGBoost, based on gradient boosting, optimizes loss by adding decision trees sequentially to minimize model errors. Its ability to handle sparse data, missing values, and resistance to overfitting makes it one of the most powerful tools for classification and regression problems. In the context of image processing, with proper pre-processing and feature extraction, XGBoost can efficiently classify images with high accuracy and speed. Logistic regression, being a linear classifier, uses a sigmoid function to predict class probabilities. It can be fast and efficient for simple datasets, but due to its linear nature, it can run into problems when working with images containing complex non-linear structures. CNNs have been specifically designed for visual data analysis and use convolution to automatically and adaptively extract features from images. However, while powerful, basic ("Vanilla") CNNs can be slower to train and require more data to achieve high accuracy compared to more optimized and deep architectures. Their effectiveness also depends on the architecture, the choice of activation function, the method of initializing the weights, and several other factors. In this work, multispectral images were taken as the original image, pre-processed by normalizing red-green-blue (RGB) layers, that is, converting multispectral images into a color image visible to the human eye. During the experiment, the training used a data set, as shown in Figure 1, which consists of two classes, such as images in which fires were detected in Figure 1(a) and without a fire in Figure 1(b). There were 163 images in each class, which were processed in combination with NDVI and NDWI vegetation indices.



(a) (b)

Figure 1. Multispectral original images: (a) image with a fire event and (b) image with an event without a fire

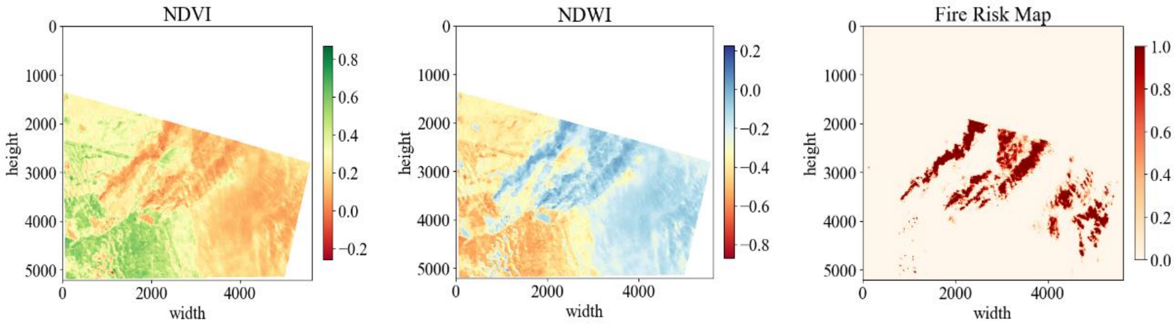
In the course of analyzing various approaches to processing geospatial data and studying the latest research in the field of remote sensing of the Earth in the field of image processing and machine learning, a combination of various vegetation indices was used to improve the accuracy of fire forecasts, as shown in Figure 2. The NDVI, or vegetation cover index, which is calculated from reflected red and near-infrared light, as shown in Figure 2(a), has long been a standard tool for assessing vegetation density and health. It is especially useful for identifying areas where vegetation is either stressed due to lack of water or, conversely, is actively developing. On the other hand, the NDWI index, which is used to determine the water stress of vegetation, allows detailed information on the water balance of vegetation, which can be critical in a pre-fire condition Figure 2(b). The combined use of these two indexes has made it possible to create a more comprehensive and informative model for identifying potential fires, which is shown in Figure 2(c).




(a) (b) (c)

Figure 2. Result when using combined processing: (a) according to vegetation indices NDVI and (b) NDWI for fire forecast, fire forecast result in the form of a risk map

The result when using the combined processing of data on the NDVI and NDWI vegetation indices for fire detection indicates the high efficiency of this methodological approach as shown in Figure 3. Figure 3(a) shows the result of using the NDVI vegetation index, and Figure 3(b) shows the result of the vegetation index NDWI. The joint use of these two indexes allowed us to create a more comprehensive and informative model for identifying fires, which is shown in Figure 3(c).




(a) (b) (c)

Figure 3. Result when using combined processing: (a) by vegetation indices NDVI and (b) NDWI for fire detection, fire detection result in the form of a risk map

The vanilla CNN model, or basic CNN, was originally designed for image processing. This model relies on the use of convolutional layers to extract key features from an image. In experimental studies, vanilla CNNs learning dynamics showed interesting features. As shown in Figure 4, the accuracy of the training set started at 55.7% at the initial epoch and reached an impressive 95.6% by the $100^{th}$ epoch. At the same time, the accuracy on the validation set also showed stable growth: from 52.5% to 93.55%, respectively. This improvement in the accuracy metric indicates that the model has successfully adapted to the data set, capturing important features and features of multispectral images.

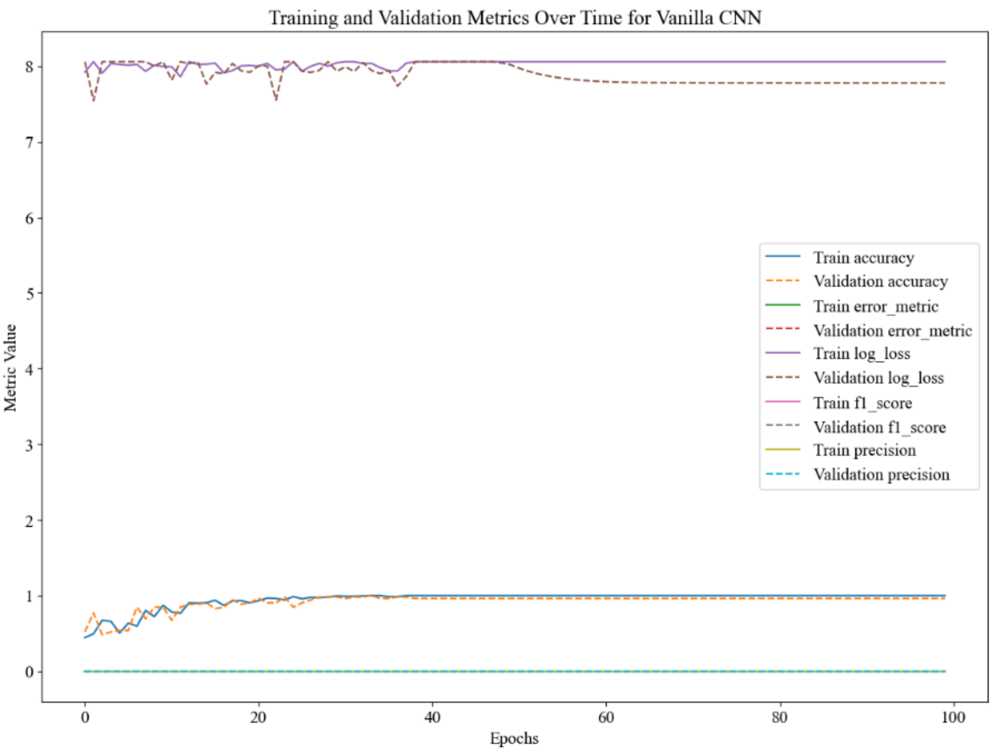



Figure 4. Vanille CNN learning evaluation

However, the most intriguing is the log loss on the training set, which remained at zero throughout the training process as shown in Figure 5. This metric requires further analysis, as the ideal log loss could indicate problems in the model or data. In the context of algorithmic complexity and computational cost, it is worth noting that CNNs require significant training resources, especially when working with large data sets. However, the results of vanilla CNN in the context of this task justify these costs.

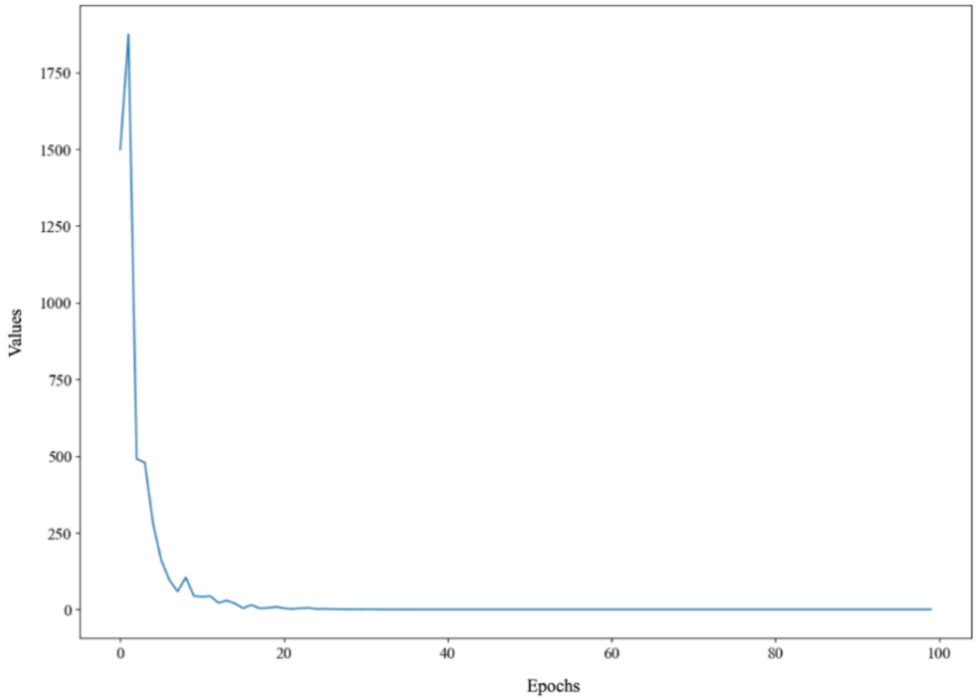



Figure 5. Vanille CNN training loss

Based on the presented data from the training results of the logistic regression model, the quality metrics and the interpretation of log loss and area under (AUC) show average values as shown in Figure 6. An AUC value close to 0.5 indicates no discriminative power, while a value close to 1 indicates high discriminative power. Here, train AUC peaks at 96.77%, which indicates a good classification of the training set, but test AUC is much lower, which may indicate a lack of generalization. A zero error on the training set may indicate that the model is overfitting. This is also confirmed by the rather high errors in the test sample. Despite the high accuracy on the training set, the accuracy on the test set suggests that the model may have difficulty predicting new data. When comparing the learning rate and after 34 training epochs, the model improved its accuracy significantly. This is due to the nature of the data, the peculiarities of the initial initialization of the weights, or the learning rate. However, it should be noted that, despite the improvement, logistic regression showed a lower learning rate compared to XGBoost. This can be explained by the inherent features of logistic regression, such as linearity and the lack of complex mechanisms for processing non-linear dependencies that XGBoost has.

Analyzing the training results of the XGBoost model, several important conclusions can be drawn regarding its effectiveness and adaptability. Observing an increase in the learning rate to 99.89% already at the second epoch, it becomes evident that XGBoost has outstanding abilities for fast convergence, see Figure 7. This property of the model is because XGBoost uses gradient boosting, optimizing each tree by reducing the errors of previous trees.

The XGBoost method was introduced due to its outstanding ability to quickly correct errors and find optimal solutions. Particular attention was paid to efficient XGBoost regularization strategies that prevent overfitting and speed up convergence. Loss analysis on the training and testing data sets confirms the excellent generalization ability of the model. Low losses on the test set indicate that the model successfully classifies most examples. The AUC value reaching 99.99% on the training set and 97.87% on the test set confirms the high discriminatory ability of the model. Comparing the results of XGBoost using logistic regression and vanilla CNN shows that the new approach with XGBoost brings additional benefits. The

XGBoost model exhibits high accuracy and low error on the training set and also demonstrates decent performance on the test set. Despite the natural increase in errors on the test set compared to the training set, they remain within acceptable limits. In general, we can say that the model successfully copes with the task, surpassing previous methods such as logistic regression and vanilla CNN.

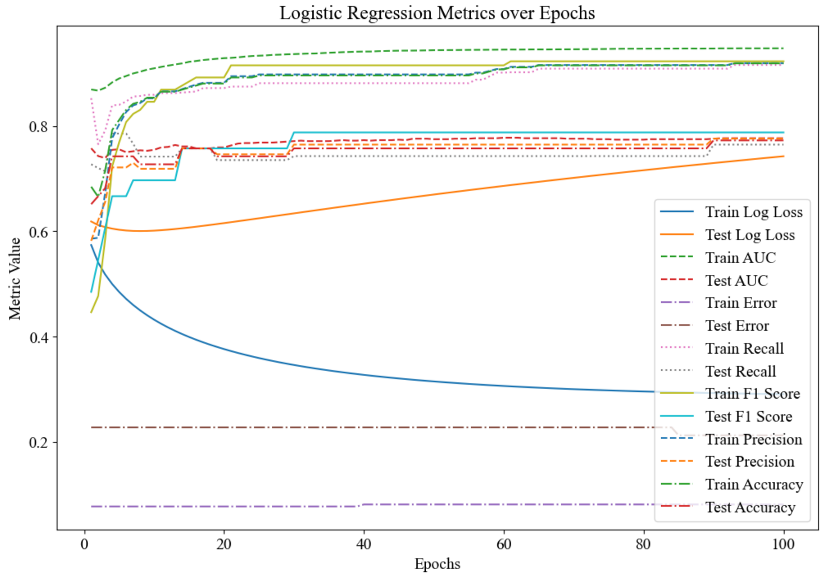



Figure 6. Evaluating the effectiveness of training logistic regression

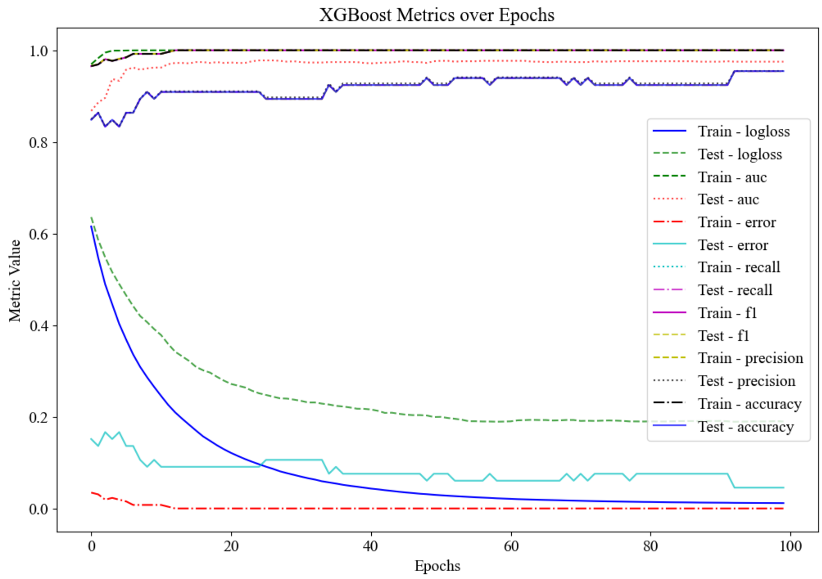



Figure 7. Evaluating the effectiveness of XGBoost training

Based on the data presented, the researchers of this work will focus on improving the generalization ability of the logistic regression model. One possible approach would be to carefully analyze the features and their impact on the model and optimize the training parameters to reduce overfitting. Perhaps the authors will consider using more complex models or a combination of models to better capture complex dependencies in the data. They may also consider introducing new features or data preprocessing methods to improve the overall performance of the model. Overall, the main emphasis is likely to be on increasing the generalizability of the model and its applicability to new data, thereby improving the practical value and applicability of research results.

## 4. CONCLUSION

Predicting and detecting fires on multispectral images using machine learning methods opens up new horizons for modern environmental safety and control of natural disasters. This study demonstrates the potential of three essential machine learning methods: XGBoost, logistic regression, and vanilla CNN in the field of Earth remote sensing. XGBoost, being a gradient-boosting method for decision trees, has shown a high learning rate and excellent prediction quality due to its way of handling missing data and built-in regularization. However, its effectiveness depends on the correct selection of parameters and the sufficiency of data for training.

Logistic regression, as a classic statistical method, has proven to be easier to apply and interpret the results, but perhaps less powerful in complex scenarios where images present complex spectral profiles and non-linear relationships. Vanilla CNN, on the other hand, uses the power of deep learning to analyze the spatial and spectral characteristics of images. Due to its ability to automatically extract features from data, CNN shows promise, especially in data-heavy scenarios.

With this in mind, the choice of the best method depends on the specific task, the availability of data, and computing resources. Multispectral images contain a wealth of information about natural objects, and machine learning techniques can help uncover hidden patterns and trends, which is the key to effective fire prediction and detection. In conclusion, we can say that modern machine learning methods are a powerful tool for processing and analyzing multispectral images, and their integration into monitoring and early fire detection systems can significantly increase the efficiency and speed of response to environmental threats.

## ACKNOWLEDGEMENT

This research has been funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan within the framework of the project BR18574092 (Development of a multi-purpose aerospace monitoring system and services for an integrated situational information presentation about emergencies in transboundary regions of the RK and the RF). The APC was funded by the project budget.

## REFERENCES

[1] N. Bagheri, "Application of aerial remote sensing technology for detection of fire blight infected pear trees," *Computers and Electronics in Agriculture*, vol. 168, Jan. 2020, doi: 10.1016/j.compag.2019.105147.

[2] L. Zhao, J. Liu, S. Peters, J. Li, S. Oliver, and N. Mueller, "Investigating the impact of using ir bands on early fire smoke detection from landsat imagery with a lightweight CNN model," *Remote Sensing*, vol. 14, no. 13, pp. 1–24, Jun. 2022, doi: 10.3390/rs14133047.

[3] D. Radočaj, M. Jurišić, and M. Gašparović, "A wildfire growth prediction and evaluation approach using Landsat and MODIS data," *Journal of Environmental Management*, vol. 304, Feb. 2022, doi: 10.1016/j.jenvman.2021.114351.

[4] R. Ghali and M. A. Akhloufi, "Deep learning approaches for wildland fires using satellite remote sensing data: detection, mapping, and prediction," *Fire*, vol. 6, no. 5, pp. 1–35, May 2023, doi: 10.3390/fire6050192.

[5] S. T. Seydi, V. Saeidi, B. Kalantar, N. Ueda, and A. A. Halin, "Fire-Net: a deep learning framework for active forest fire detection," *Journal of Sensors*, vol. 2022, Feb. 2022, doi: 10.1155/2022/8044390.

[6] M. Luo *et al.*, "Combination of feature selection and catboost for prediction: the first application to the estimation of aboveground biomass," *Forests*, vol. 12, no. 2, Feb. 2021, doi: 10.3390/f12020216.

[7] X. Hu, Y. Ban, and A. Nascetti, "Uni-temporal multispectral imagery for burned area mapping with deep learning," *Remote Sensing*, vol. 13, no. 8, Apr. 2021, doi: 10.3390/rs13081509.

[8] M. Aamir *et al.*, "Natural disasters intensity analysis and classification based on multispectral images using multi-layered deep convolutional neural network," *Sensors*, vol. 21, no. 8, Apr. 2021, doi: 10.3390/s21082648.

[9] T. Kacker, A. Perrusquia, and W. Guo, "Multi-spectral fusion using generative adversarial networks for UAV detection of wild fires," in *2023 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, Feb. 2023, pp. 182–187, doi: 10.1109/ICAIIC57133.2023.10067042.

[10] S. Wang *et al.*, "Using soil library hyperspectral reflectance and machine learning to predict soil organic carbon: Assessing potential of airborne and spaceborne optical soil sensing," *Remote Sensing of Environment*, vol. 271, p. 112914, Mar. 2022, doi: 10.1016/j.rse.2022.112914.

[11] J. Kang, S. Tariq, H. Oh, and S. S. Woo, "A survey of deep learning-based object detection methods and datasets for overhead imagery," *IEEE Access*, vol. 10, pp. 20118–20134, 2022, doi: 10.1109/ACCESS.2022.3149052.

[12] M. Grari *et al.*, "Using IoT and ML for forest fire detection, monitoring, and prediction: a literature review," *Journal of Theoretical and Applied Information Technology*, vol. 100, no. 19, pp. 5445–5461, 2022.

[13] M. Sobhana, S. C. Chaparala, D. N. V. S. L. S. Indira, and K. K. Kumar, "A disaster classification application using convolutional neural network by performing data augmentation," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 27, no. 3, p. 1712, Sep. 2022, doi: 10.11591/ijeecs.v27.i3.pp1712-1720.

[14] D. Xiao, Y. Pan, J. Feng, J. Yin, Y. Liu, and L. He, "Remote sensing detection algorithm for apple fire blight based on UAV multispectral image," *Computers and Electronics in Agriculture*, vol. 199, Aug. 2022, doi: 10.1016/j.compag.2022.107137.

[15] C. Sun, "Analyzing multispectral satellite imagery of south American wildfires using deep learning," in *2022 International Conference on Applied Artificial Intelligence (ICAPAI)*, May 2022, pp. 1–6, doi: 10.1109/ICAPAI55158.2022.9801567.

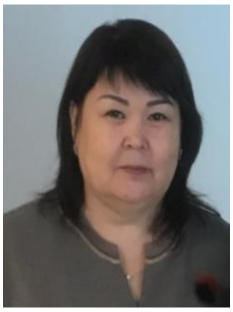
[16] S. Saha, B. Bera, P. K. Shit, S. Bhattacharjee, and N. Sengupta, "Prediction of forest fire susceptibility applying machine and deep

learning algorithms for conservation priorities of forest resources," *Remote Sensing Applications: Society and Environment*, vol. 29, Jan. 2023, doi: 10.1016/j.rsase.2022.100917.
[17] B. Kalantar, N. Ueda, M. O. Idrees, S. Janizadeh, K. Ahmadi, and F. Shabani, "Forest fire susceptibility prediction based on machine learning models with resampling algorithms on remote sensing data," *Remote Sensing*, vol. 12, no. 22, Nov. 2020, doi: 10.3390/rs12223682.
[18] D. Rashkovetsky, F. Mauracher, M. Langer, and M. Schmitt, "Wildfire detection from multisensor satellite imagery using deep semantic segmentation," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 7001–7016, 2021, doi: 10.1109/JSTARS.2021.3093625.
[19] N. T. Toan, P. Thanh Cong, N. Q. Viet Hung, and J. Jo, "A deep learning approach for early wildfire detection from hyperspectral satellite images," in *2019 7th International Conference on Robot Intelligence Technology and Applications (RiTA)*, Nov. 2019, pp. 38–45, doi: 10.1109/RITAPP.2019.8932740.
[20] M. Yessenova *et al.*, "Application of informative textural Law's masks methods for processing space images," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 4, pp. 4557-4566, Aug. 2023, doi: 10.11591/ijece.v13i4.pp4557-4566.
[21] G. Abdikerimova *et al.*, "Applying textural Law's masks to images using machine learning," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 5, pp. 5569–5575, Oct. 2023, doi: 10.11591/ijece.v13i5.pp5569-5575.
[22] M. Yessenova *et al.*, "Identification of factors that negatively affect the growth of agricultural crops by methods of orthogonal transformations," *Eastern-European Journal of Enterprise Technologies*, vol. 3, no. 2 (117), pp. 39–47, Jun. 2022, doi: 10.15587/1729-4061.2022.257431.
[23] M. Yessenova *et al.*, "The effectiveness of methods and algorithms for detecting and isolating factors that negatively affect the growth of crops," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 2, pp. 1669–1679, Apr. 2023, doi: 10.11591/ijece.v13i2.pp1669-1679.
[24] M. Yessenova *et al.*, "The applicability of informative textural features for the detection of factors negatively influencing the growth of wheat on aerial images," *Eastern-European Journal of Enterprise Technologies*, vol. 4, no. 2(118), pp. 51–58, Aug. 2022, doi: 10.15587/1729-4061.2022.263433.
[25] M. Yessenova *et al.*, "Features of growth of agricultural crops and factors negatively affecting their growth," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 30, no. 1, pp. 625–632, Apr. 2023, doi: 10.11591/ijeecs.v30.i1.pp625-632.

## BIOGRAPHIES OF AUTHORS

**Murat Aitimov** Ph.D in philosophy of instrumentation. Dr. Aitimov Murat is an accomplished scholar with a rich academic background. He currently serves as the Director of the Kyzylorda Regional Branch at the Academy of Public Administration under the President of the Republic of Kazakhstan. With an impressive 28 years of experience in both scientific research and pedagogy, Dr. Murat is a recognized authority in his field. His contributions to academia are significant, as evidenced by his substantial body of work. He has authored 55 scientific articles, a testament to his dedication to advancing knowledge. Notably, 7 of his articles have been featured on Scopus, highlighting their impact and relevance in the global research community. In addition to his articles, Dr. Murat has authored three influential books. He also holds an innovation patent in the realm of instrumentation and information systems, showcasing his multidimensional expertise. His expertise and insights continue to drive progress in the field of instrumentation, making him a valuable resource for researchers and academics alike. For those seeking to connect with Dr. Aitimov Murat, he can be reached at email: aitimovmurat07@gmail.com.

**Mira Kaldarova** graduated in 2023 from the doctoral program in the educational programs-D094 information technology from Department of Computer Engineering and Software Seifullin Kazakh Agro Technical Research University. Currently, she is a senior lecture, Higher School of Information Technology and Engineering Astana International University Kabanbay Batyra ave, 8, Astana, Republic of Kazakhstan. Her research interests include mathematical modeling, bioinformatics, artificial intelligence and data mining. She can be contacted at email: kmiraj8206@gmail.com.



**Akmaral Kassymova** candidate of pedagogical sciences, currently works at Zhangir Khan University at the Department of Information Technology, Professor. He has more than 39 years of scientific and pedagogical experience and more than 100 scientific papers, including 9 articles in the Scopus database, 20 teaching aids. She can be contacted at email: kasimova_ah@mail.ru.

**Kaiyrbek Makulov** currently working at Caspian University of Technology and Engineering Named after Sh. Yessenov. He is the Vice President for Academic Affairs. His scientific interests are "information technologies and systems", "improving information support for public administration in the Republic of Kazakhstan". Completed a scientific internship under the Bolashak program in the specialty "information technologies and systems" (Barcelona, Spain). Completed advanced training in IT areas in countries such as United Kingdom (London), Portugal (Lisboa), Spain (Barcelona), Russian Federation (St. Petersburg). He can be contacted at email: kaiyrbek.makulov@yu.edu.kz.

**Raikhan Muratkhan** in 2002 he graduated from the Karaganda State University named after E.A. Buketov with a degree in Applied Mathematics. In 2019 he defended her dissertation in the specialty "6D060200–computer sciences" and received a Ph.D. Currently, he is Associate Professor at the Department of Applied mathematics and Informatica of Karaganda Buketov University. He is the author of more than 70 scientific papers, including 1 monographs, 8 articles in the Scopus database. Scientific interests-image processing, pattern recognition theory, data mining, information security. He can be contacted at email: raikhan.muratkhan@mail.ksu.kz.

**Serik Nurakynov** from 2009 to the present time he has been working at the Institute of Ionosphere. He has more than 35 scientific publications, 7 of them in journals included in the Scopus and Web of Science databases, 20 in scientific publications recommended by the Committee for Quality Assurance in Science and Higher Education of the Ministry of Education and Science of the Republic of Kazakhstan. Scientific interests: optical and SAR image processing, GIS, emergency monitoring, cryosphere, lithosphere-atmosphere-ionosphere coupling. He can be contacted at email: ionos@ionos.kz.

**Nurmakhambet Sydyk** PhD-doctoral student in the specialty "space technique and technology" at Al-Farabi Kazakh National University, master's degree in "engineering and technology". Currently he is the head of the Cartography and GIS Laboratory at the Institute of Ionosphere. He has published more than 10 scientific papers in the GIS, emergency monitoring, cryosphere and geomechanics spheres, 4 articles in the Scopus and Web of Science databases. Scientific interests: optical and SAR image processing, cryosphere, GIS, geomechanics, geodynamics, emergency monitoring. He can be contacted at email: nurmakhambet.sydyk@ionos.kz.

**Ideyat Bapiyev** PhD in the specialty "information systems", currently works at Zhangir Khan University at the Department of Information Technology, associate professor. He has more than 25 years of scientific and pedagogical experience and more than 50 scientific papers, including 11 articles in the Scopus database, 10 teaching aids. She can be contacted at email: bapiev@mail.ru.