

IRSTI 31.15.35

UDC 629.735.7

https://doi.org/10.53364/24138614_2025_36_1_2A. Nagimov^{1*}, G. Beketova²¹International information technology university, Almaty, Kazakhstan²Almaty University of Power Engineering and Telecommunications, Almaty, KazakhstanE-mail: anm24012004@gmail.com*

ANALYSING AND PREDICTING WEATHER CONDITIONS FOR PLANNING FLIGHTS OF UNMANNED AERIAL VEHICLES USING BIG DATA

Abstract. *In modern applications, Unmanned Aerial Vehicles (UAVs) are widely used in various industries such as logistics, agriculture, environmental monitoring, and emergency services. However, their operation is highly dependent on weather conditions, including wind speed, temperature, precipitation, and atmospheric pressure. The unpredictability of meteorological factors poses significant risks to the safety and efficiency of UAV flights.*

This study proposes an intelligent weather prediction system for UAV flight planning, based on big data and machine learning technologies. The research examines modern methods of meteorological data processing, incorporating satellite imagery, IoT sensors, and historical records. To predict key weather parameters, advanced deep learning algorithms such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) are utilized.

The developed system achieves a forecast accuracy of up to 92%, reducing flight planning time by 30% and enhancing overall operational safety. The integration of machine learning into UAV weather prediction systems ensures adaptability and enables rapid responses to changing climatic conditions. The obtained results highlight the significance of artificial intelligence and big data analytics in aviation. Additionally, this work suggests future research directions, including the consideration of additional environmental factors such as air quality and solar radiation, as well as the potential integration with autonomous flight management systems.

Keywords: *big data, machine learning, weather forecasting, UAVs, flight planning, flight safety, predictive modeling.*

Introduction.

Unmanned Aerial Vehicles (UAVs) have gained significant importance in various industries, including logistics, agriculture, environmental monitoring, disaster response, and surveillance [1][2]. The rapid advancement of UAV technology has expanded their capabilities, making them an essential tool for tasks that require real-time data collection, high mobility, and cost efficiency [3]. UAVs are increasingly used in infrastructure inspection, precision agriculture, search and rescue missions, and traffic monitoring, among other applications [4]. Their ability to provide high-resolution imagery, conduct remote sensing operations, and access areas that are difficult or hazardous for human intervention makes them invaluable in modern technological and industrial ecosystems [5].

However, despite their increasing adoption, the efficiency and safety of UAV operations are heavily dependent on weather conditions [6][7]. Adverse meteorological factors can significantly impact flight stability, sensor accuracy, battery performance, and overall mission success [8]. Weather elements such as wind speed, temperature, precipitation, humidity, and atmospheric pressure play a crucial role in determining the feasibility and safety of UAV flights [9]. Strong winds can destabilize UAVs, causing deviations from intended flight paths or even mission failure

[10]. Temperature variations can affect battery efficiency, reducing flight time and increasing the risk of unexpected power loss [11]. Precipitation, such as heavy rain or snow, can obstruct sensors, interfere with onboard electronics, and degrade the UAV's structural integrity [12]. Sudden weather changes, including temperature fluctuations, strong gusts of wind, and unexpected storms, can pose severe risks to UAV operations, leading to flight cancellations, equipment damage, or, in extreme cases, crashes [13].

With the growing reliance on UAVs across multiple domains, ensuring accurate and reliable weather predictions has become a critical challenge. Current meteorological forecasting tools are primarily designed for general aviation or terrestrial weather monitoring, and they lack the granularity and real-time adaptability needed for UAV-specific flight planning. Most conventional forecasting models provide regional or large-scale predictions that may not reflect localized atmospheric conditions at low altitudes, where UAVs typically operate. Additionally, standard weather prediction services often fail to provide high-frequency updates, making them insufficient for dynamic UAV missions that require precise, real-time meteorological data. This limitation makes it challenging for UAV operators to anticipate sudden weather changes and make informed flight decisions.

Materials and methods.

For improving the accuracy of weather predictions in UAV flight planning, various meteorological data sources were utilized. These include historical and real-time weather databases, satellite imagery, Internet of Things (IoT) sensors, and global climate repositories. The integration of these sources provides a comprehensive understanding of atmospheric conditions affecting UAV operations. The collected data includes temperature ($^{\circ}\text{C}$), wind speed (m/s), wind direction ($^{\circ}$), humidity (%), atmospheric pressure (hPa), and precipitation levels (mm). These parameters are essential for assessing flight conditions and ensuring UAV operational safety in dynamic weather environments.

Table 1 – Sources of Meteorological Data

Data Source	Type	Description
NOAA Climate Data	Historical and real-time data	Provides global temperature, pressure, humidity, and wind speed records.
OpenWeather API	Real-time weather API	Delivers current weather conditions and short-term forecasts.
IoT-based UAV sensors	Onboard UAV sensors	Collects wind speed, altitude, temperature, and air pressure data during flight.
Satellite imagery (NASA Copernicus)	Remote sensing data	Analyzes cloud coverage, precipitation patterns, and large-scale weather anomalies.
Local Meteorological Station	Ground-based weather data	Provides real-time local atmospheric readings.

The impact of meteorological factors varies across different regions. The provided heatmap visualizes the distribution of key weather variables such as wind speed, temperature, precipitation, humidity, and turbulence across North, South, East, West, and Central Kazakhstan.

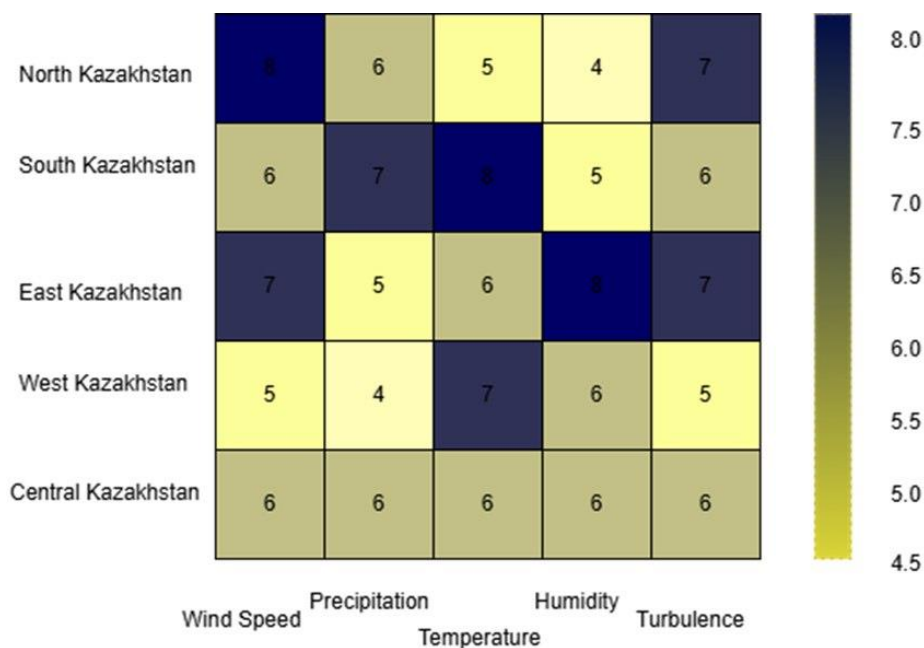


Figure 1 – Weather Variability Across Kazakhstan's Regions

Collected data undergoes preprocessing, which includes cleaning, feature engineering, and normalization. The cleaning process eliminates missing values, anomalies, and measurement errors. Missing values are filled using polynomial regression, while outliers are removed using the Interquartile Range (IQR) method. Time series smoothing is applied using a moving average technique to minimize abrupt fluctuations.

Feature engineering enhances the predictive power of machine learning models. Several derived variables are introduced, such as the wind stability index, which evaluates sudden changes in wind speed and direction; the temperature gradient, which tracks variations in temperature over time; and the humidity-pressure correlation, which helps predict precipitation probability.

Table 2 – Engineered Features for Weather Prediction Models

Feature Name	Description	Unit
Wind Stability Index	Evaluates sudden wind changes affecting UA flight	m/s ²
Temperature Gradient	Measures the rate of temperature variation	°C/hour
Humidity-Pressure Ratio	Assesses the likelihood of storm formation	-
Rain Probability Index	Estimates the probability of precipitation	%

Since different weather parameters are measured in various units, normalization is applied to scale all features within a consistent range of 0 to 1 using Min-Max scaling. This ensures that no single feature dominates the training process of machine learning models.

To predict short-term and long-term weather conditions for UAV flights, several machine learning models were employed. Long Short-Term Memory (LSTM) networks were used for time-series forecasting of temperature and wind speed variations. Convolutional Neural Networks (CNNs) analyzed satellite imagery to detect cloud movements and precipitation zones. Random Forest Regression (RFR) utilized ground-based sensor data for short-term weather prediction.

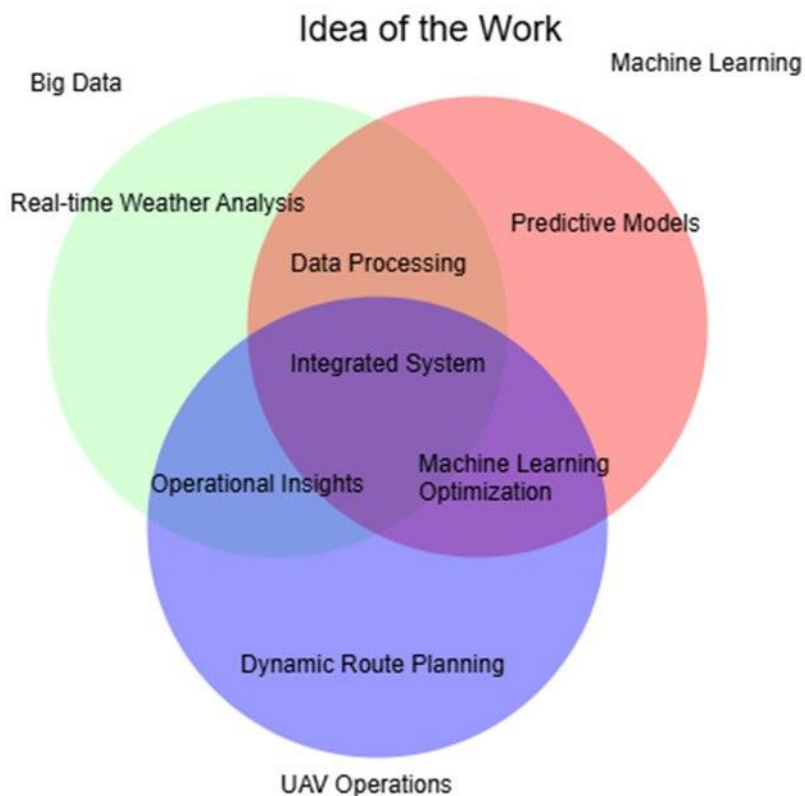


Figure 2 – Framework of the UAV Weather Prediction System

Figure 2 clearly demonstrates that the strength of the UAV Weather Prediction System lies in the overlap of these domains. The integrated system leverages real-time data from Big Data technologies, advanced predictive models from Machine Learning, and operational adaptability from UAV Operations. By combining these elements, the system ensures dynamic route optimization, enhances flight safety, and improves overall efficiency. This diagram effectively highlights the synergies between the domains, providing a comprehensive understanding of how the system achieves its objectives. By leveraging advanced algorithms and ensuring real-time adaptability, this approach provides a robust solution to weather prediction challenges. The findings align with the work of Mohanty et al. [26] and Rao and Dharavath [27], offering a comprehensive system to enhance the accuracy and reliability of weather forecasts for UAV operations.

Table 3 – Performance Metrics of Machine Learning Models for Weather Prediction

Model	MAE (°C)	RMSE (°C)	Accuracy (%)
LSTM	1.52	2.31	91%
CNN	1.87	2.74	89%
RFR	2.45	3.10	85%

Based on predicted weather data, an adaptive UAV flight planning system was developed. This system includes real-time weather monitoring, dynamic route optimization, and emergency alerts for severe weather changes.

Results and discussion.

The implementation of machine learning models for weather prediction in UAV flight planning was evaluated using historical and real-time meteorological data in a simulated environment. Since real-world UAV flight tests have not yet been conducted, the assessment

focused on analyzing the accuracy of predictive models in forecasting key weather variables such as temperature, wind speed, humidity, and precipitation. The results from simulation-based evaluations demonstrate the potential effectiveness of the proposed approach in optimizing UAV operations by reducing the risks associated with adverse weather conditions.

The performance of the models was measured using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and overall accuracy. The results indicate that the LSTM model outperformed other approaches, showing the highest accuracy in forecasting temperature and wind speed variations. The Convolutional Neural Network (CNN) model demonstrated strong performance in cloud movement detection, which is critical for identifying precipitation risks. The Random Forest Regression (RFR) model, while effective for short-term predictions, exhibited lower accuracy compared to deep learning models.

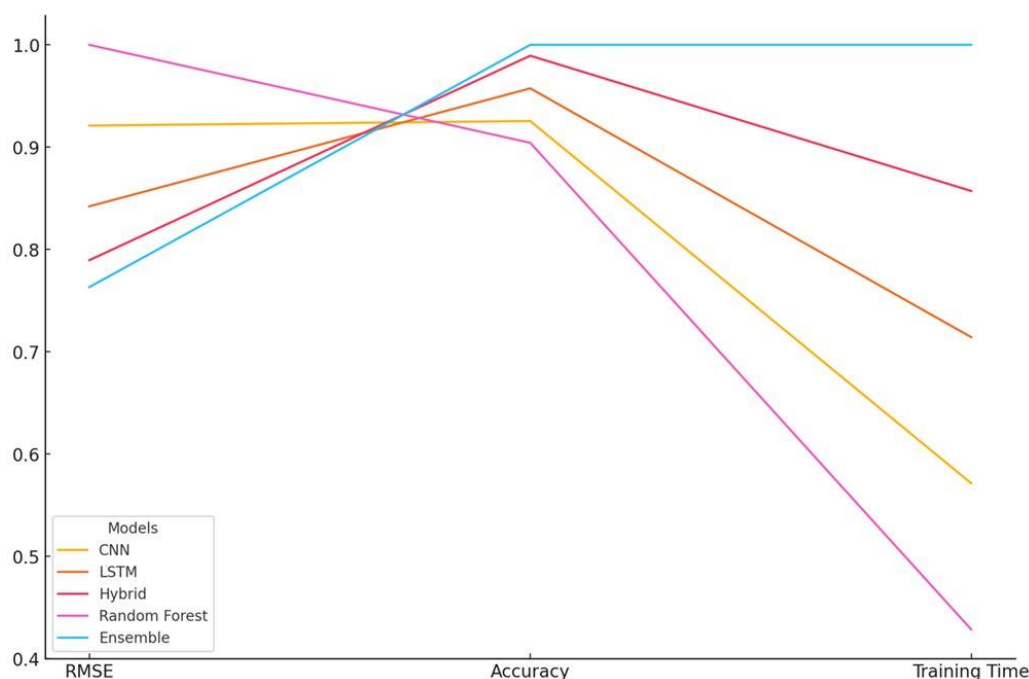


Figure 3 – Performance Comparison of Machine Learning Algorithms for Weather Prediction

Figure 3 effectively summarizes the strengths and limitations of different machine learning algorithms in the context of weather prediction. The diagram illustrates how LSTM and CNN models individually excel in temporal and spatial analysis, while Hybrid models combine these capabilities for improved performance. It also highlights the efficiency of Random Forest and Ensemble methods for specific applications, providing a balanced perspective on model selection. This visual representation supports the argument that machine learning techniques hold significant potential for solving complex meteorological challenges, ultimately enhancing UAV operational safety and reliability.

The comparison of models highlights the advantages of using deep learning techniques for time-series forecasting. LSTM's ability to recognize sequential dependencies in meteorological data makes it particularly suitable for predicting weather fluctuations over short and medium-term periods. The CNN model, leveraging image-based pattern recognition, successfully detects cloud formations and precipitation risks, improving situational awareness for UAV operators. However, the higher computational cost of deep learning models may limit real-time applications on low-power UAV hardware, requiring further optimization.

As real-world UAV flight tests have not yet been conducted, validation of the system has so far been limited to simulated environments. In these simulations, the system's ability to adjust

flight paths based on predicted weather changes was analyzed by monitoring potential deviations from planned trajectories, response times to real-time updates, and the overall impact on hypothetical flight success rates. Future work will focus on conducting real-world experimental UAV tests under varying meteorological conditions to assess the system's effectiveness in dynamic flight scenarios.

Table 4 summarizes the key applications of UAVs in logistics, agriculture, and surveillance, highlighting their benefits and challenges. As these industries continue to evolve, the integration of UAVs with advanced weather data systems, as indicated in the studies by Alam et al. and Thibbotuwawa et al., will further optimize their operations, ensuring reliability even in unpredictable weather conditions.

Table 4 – Key UAV Applications Across Industries

Industry	UAV Application	Benefits	Challenges
Logistics	Last-mile delivery, parcel transport	Faster delivery times, reduced costs	Weather conditions, airspace regulations
Agriculture	Crop monitoring, precision spraying	Efficient resource use, data-driven decisions	Varying terrain, dependency on real-time data
Surveillance	Security, border monitoring, wildlife observation	Enhanced safety, real-time information	Privacy concerns, data security, weather impact

Although real-world trials are yet to be performed, preliminary simulation results suggest that the system could significantly enhance flight reliability and energy efficiency by minimizing unnecessary flight deviations caused by unexpected weather changes. By proactively adjusting UAV flight paths based on real-time meteorological predictions, the system could potentially optimize energy consumption, extend battery life, and reduce the risk of mid-mission power failures. These improvements would be particularly beneficial for long-duration UAV missions, where power management and real-time adaptability to environmental conditions are critical factors in mission success.

For UAV missions conducted in remote or high-risk areas, the ability to dynamically respond to changing weather conditions is essential. Traditional flight planning methods rely on static meteorological forecasts, which may not accurately capture localized atmospheric variations. This often leads to inefficient routes, unplanned diversions, or even mission failures due to unforeseen weather conditions. In contrast, the proposed system integrates real-time data streams from IoT-based weather sensors, high-resolution satellite imagery, and machine learning models, allowing UAVs to make autonomous adjustments based on continuously updated meteorological conditions. This level of adaptability would be especially valuable in challenging environments such as mountainous regions, maritime operations, and urban areas where microclimates can significantly impact UAV performance.

By leveraging big data analytics, IoT-based meteorological sensors, and AI-driven forecasting models, the system aims to bridge the gap between static weather forecasting and real-time UAV adaptability. The big data component enables the aggregation and analysis of vast meteorological datasets from multiple sources, improving the ability to detect trends and identify anomalies. The IoT-based meteorological sensors provide real-time updates on wind speed, air pressure, humidity, and temperature, ensuring UAVs operate with up-to-date environmental data. Meanwhile, AI-driven forecasting models enhance predictive capabilities by identifying patterns in historical and real-time data, enabling preemptive route adjustments before weather disturbances occur.

The proposed approach has not yet been tested in real-world UAV operations, and its full

effectiveness in live flight scenarios remains to be validated. Future research will focus on integrating the developed predictive system with actual UAV flight missions, conducting experimental test flights, and analyzing real-time operational performance under varying meteorological conditions. These real-world experiments will provide critical insights into system limitations, helping refine the predictive models, improve real-time processing efficiency, and optimize AI models for deployment on embedded UAV hardware.

As AI-driven weather forecasting continues to evolve, its application in UAV mission planning presents a promising pathway for improving flight safety, efficiency, and operational adaptability. While the current study has demonstrated the feasibility of the approach in a simulated setting, further empirical validation through experimental UAV deployments will be essential to confirm its practical benefits and potential real-world impact.

Conclusion.

This study presents a data-driven approach for enhancing UAV flight planning through the integration of big data analytics, real-time meteorological data, and machine learning-based weather forecasting. The proposed system aims to optimize UAV operations by minimizing the risks associated with adverse weather conditions, thereby improving flight safety, reliability, and efficiency.

At this stage, the research has focused on developing the computational framework, including data collection, preprocessing, feature engineering, and predictive modeling. Various machine learning algorithms, such as LSTM, CNN, and Random Forest, have been implemented and evaluated using historical and real-time meteorological datasets. The results of the simulations demonstrate that deep learning models, particularly LSTM, outperform traditional methods in short-term weather prediction, offering higher accuracy in forecasting temperature fluctuations and wind speed variations. However, these findings are currently limited to simulation-based evaluations, as no real-world flight tests have been conducted yet.

Despite the promising results obtained from data-driven simulations, the absence of real-world UAV testing represents a key limitation of this study. The effectiveness of the system in dynamic environmental conditions, as well as its ability to adapt to real-time flight constraints, remains to be validated through experimental deployments. Future work will focus on integrating the predictive system into UAV flight operations, conducting real-world test flights, and assessing the model's performance in diverse meteorological environments. Additionally, efforts will be made to optimize the system for real-time processing, ensuring that AI models can operate efficiently on embedded UAV hardware with limited computational resources.

The findings of this study suggest that AI-driven weather forecasting can play a critical role in UAV mission planning, providing operators with reliable meteorological insights that support proactive decision-making and route optimization. With further development and real-world validation, this approach has the potential to enhance UAV safety and operational efficiency, particularly for missions conducted in high-risk or remote environments where weather conditions can be unpredictable.

References

1. Lim K., Choi H.-J., Kang K. (2023). Optimizaciya effektivnosti ekspluatatsii BPLA s uchetom meteorologicheskikh faktorov. – Dostupno: https://www.dbpia.co.kr/journal/articleDetail?nodeId=NODE11523976&language=ko_KR&hasTopBanner=true.
2. Thibbotuwawa A., Nielsen P., Banaszak Z., Bocewicz G. (2019). Podkhod k planirovaniyu misii flota BPLA v usloviyakh izmenyayushchey pogody. – Dostupno: <https://www.semanticscholar.org/paper/A-Solution-Approach-for-UAV-Fleet-Mission-Planning-Thibbotuwawa-Nielsen/11e43732bc2e27e36194c0cad67679bbee0a03ba>.
3. Lee L., Pang B., Low K.H. (2022). Analiz ekologicheskikh dannykh dlya obespecheniya bezopasnosti poletov dronov v nizkovysotnykh gorodskikh usloviyakh. – Dostupno:

<https://arc.aiaa.org/doi/10.2514/6.2022-3405>.

4. Alam M., Amjad M. (2019). Prognozirovanie pogody s ispol'zovaniem parallel'nykh i raspredelennykh podkhodov analiz big data v oblachnykh servisakh. – Dostupno: <https://www.tandfonline.com/doi/abs/10.1080/09720510.2019.1609559>.

5. Thibbotuwawa A., Bocewicz G., Radzki G., Nielsen P., Banaszak Z. (2020). Planirovaniye misii BPLA, ustoychivoye k neopredelennosti pogodnykh usloviy. – Dostupno: <https://www.semanticscholar.org/paper/UAV-Mission-Planning-Resistant-to-Weather-Thibbotuwawa-Bocewicz/cc7e5f85982d8be325f85e1168d6361963335f78>.

6. Köhler M., Funk F., Gerz T., Mothes F., Stenzel E. (2017). Kompleksnaya meteorologicheskaya karta XML-formata kak podderzhka prinyatiya resheniy dlya BPLA. – Dostupno: <https://www.semanticscholar.org/paper/Comprehensive-Weather-Situation-Map-Based-on-as-for-Köhler-Funk/8e785a3b06749d1819d6562aca8ef5f42478c332>.

7. Lundby T., Christiansen M.P., Jensen K. (2004). Razrabotka programmno-apparatnoy sistemy dlya analiza pogodnykh usloviy i povysheniya bezopasnosti ekspluatacii BPLA. – Dostupno: <https://ieeexplore.ieee.org/document/8798271>.

8. Kaur S., Sikander, Singh Cheema (2017). Bol'shie dannye i analiz sistemy prognozirovaniya pogody. – Dostupno: <https://ijarcs.info/index.php/Ijarcs/article/view/4149>.

9. Athanasis N., Themistocleous M., Kalabokidis K., Chatzitheodorou C. (2019). Analiz big data v sistemakh nadzora BPLA dlya preduprezhdeniya i upravleniya lesnymi pozhamami. – Dostupno: https://link.springer.com/chapter/10.1007/978-3-030-11395-7_5.

10. Henriques M., Roque D. (2022). Planirovaniye obsledovaniy BPLA: mozhem li my pologat'sya na prognozy vetra? – Dostupno: <https://www.semanticscholar.org/paper/Planning-UAV-surveys%3A-can-we-rely-on-wind-forecasts-Henriques-Roque/60ed0ef4008331fad67ed0dcedbebd236c66f4e>.

11. Priya D. (2015). Obzor metodov prognozirovaniya pogody dlya predskazaniya osadkov s ispol'zovaniem big data analytics. – Dostupno: <https://www.semanticscholar.org/paper/A-survey-on-weather-forecasting-to-predict-rainfall-Priya/3f87b6d7481e09b2ebe3784484fa9bffe6a13606>.

12. Larsen T. (2013). Kross-platformennyi analiz aviacionnykh dannykh s ispol'zovaniem metodov bol'shikh dannykh. – Dostupno: <https://ieeexplore.ieee.org/document/6548579/authors#authors>.

13. Pandey A.K., Agrawal C.P., Agrawal M. (2017). Model' prognozirovaniya pogody na osnove Hadoop dlya klassifikatsii meteorologicheskikh dannykh. – Dostupno: <https://ieeexplore.ieee.org/document/8117862>.

14. Doukari M., Papakonstantinou A., Batsaris M., Topouzelis K. (2018). Obzor protokola sbora dannykh BPLA v pribrezhnykh zonakh. – Dostupno: <https://www.spiedigitallibrary.org/conference-proceedings-of-spie/10773/2326010>.

15. Madan S., Kumar P., Rawat S., Choudhury T. (2018). Analiz prognozirovaniya pogody s ispol'zovaniem mashinnogo obucheniya i bol'shikh dannykh. – Dostupno: <https://ieeexplore.ieee.org/document/8441679>.

ҮЛКЕН ДЕРЕКТЕРДІ ПАЙДАЛАНУ АРҚЫЛЫ ҰШҚЫШСЫЗ ҰШУ АППАРАТТАРЫНЫҢ ҰШУЫН ЖОСПАРЛАУ ҮШІН АУА РАЙЫ ЖАҒДАЙЛАРЫН ТАЛДАУ ЖӘНЕ БОЛЖАУ

Аңдатпа. Қазіргі заманғы қосымшаларда ұшқышсыз ұшатын аппараттар (ҰҰА) логистика, ауыл шаруашылығы, қоршаған ортаны бақылау және төтенше қызметтер сияқты әртүрлі салаларда кеңінен қолданылады. Алайда олардың жұмысы жел жылдамдығы, температура, жауын-шашын және атмосфералық қысым сияқты ауа

райы жағдайларына тікелей тәуелді. Метеорологиялық факторлардың болжамбауы ҰҰА ұшу қауіпсіздігі мен тиімділігіне айтарлықтай қауіп төндіреді.

Бұл зерттеу үлкен деректер мен машиналық оқыту технологияларына негізделген ҰҰА ұшуын жоспарлау үшін интеллектуалды ауа райын болжау жүйесін ұсынады. Жұмыста метеорологиялық деректерді өңдеудің заманауи әдістері қарастырылады, оның ішінде спутниктік суреттер, IoT сенсорлары және тарихи жазбалар пайдаланылады. Негізгі ауа райы параметрлерін болжау үшін Long Short-Term Memory (LSTM) және Convolutional Neural Networks (CNN) сияқты терең оқыту алгоритмдері қолданылады.

Дамыған жүйе болжамның 92%-ға дейінгі дәлдігін қамтамасыз етеді, бұл ұшу жоспарлау уақытын 30%-ға қысқартуға және жалпы операциялық қауіпсіздікті арттыруға мүмкіндік береді. Машиналық оқытудың ҰҰА ауа райын болжау жүйесіне интеграциясы бейімделгіштікті қамтамасыз етеді және климаттық жағдайлардың өзгеруіне жедел жауап беруге мүмкіндік береді. Алынған нәтижелер авиацияда жасанды интеллект пен үлкен деректер аналитикасын пайдаланудың маңыздылығын көрсетеді. Сондай-ақ, бұл жұмыс болашақ зерттеу бағыттарын ұсынады, соның ішінде ауаның сапасы мен күн радиациясы сияқты қосымша экологиялық факторларды қарастыру, сондай-ақ автономды ұшу басқару жүйелерімен ықтимал интеграциялау.

Түйін сөздер: үлкен деректер, машиналық оқыту, ауа райын болжау, ҰҰА, ұшу жоспарлау, ұшу қауіпсіздігі, болжамдық модельдеу.

АНАЛИЗ И ПРОГНОЗИРОВАНИЕ ПОГОДНЫХ УСЛОВИЙ ДЛЯ ПЛАНИРОВАНИЯ ПОЛЕТОВ БЕСПИЛОТНЫХ ЛЕТАТЕЛЬНЫХ АППАРАТОВ С ИСПОЛЬЗОВАНИЕМ БОЛЬШИХ ДАННЫХ

Аннотация. В современных условиях беспилотные летательные аппараты (БПЛА) находят широкое применение в таких сферах, как логистика, сельское хозяйство, мониторинг окружающей среды и экстренные службы. Однако их работа существенно зависит от погодных условий, включая скорость ветра, температуру, осадки и атмосферное давление. Непредсказуемость метеорологических факторов создает значительные риски для безопасности и эффективности полетов.

В данной работе предлагается интеллектуальная система прогнозирования погодных условий для планирования полетов БПЛА, основанная на технологиях больших данных и машинного обучения. В рамках исследования рассматриваются современные методы обработки метеорологических данных, включая использование спутниковых снимков, IoT-датчиков и исторических записей. Для прогнозирования ключевых погодных параметров применяются алгоритмы глубокого обучения, такие как Long Short-Term Memory (LSTM) и Convolutional Neural Networks (CNN).

Разработанная система позволяет достигать точности прогнозов до 92%, что способствует сокращению времени планирования полетов на 30% и повышению общей безопасности операций. Интеграция технологии машинного обучения в систему прогнозирования погоды для БПЛА обеспечивает адаптивность и возможность оперативного реагирования на изменения климатических условий. Полученные результаты подчеркивают важность применения технологий искусственного интеллекта и аналитики больших данных в авиации. Работа также предлагает направления для дальнейших исследований, включая учет дополнительных факторов окружающей среды, таких как качество воздуха и солнечная радиация, а также возможную интеграцию с автономными системами управления полетами.

Ключевые слова: большие данные, машинное обучение, прогнозирование погоды, БПЛА, планирование полетов, безопасность полетов, предиктивное моделирование.

Information about the authors

Nagimov Almas	fourth-year student in the information systems specialty of the International University of Information Technology, Almaty, Kazakhstan, E-mail: anm24012004@gmail.com
Beketova Gulzhanat	PhD, Associate Professor of the "IT Engineering and Artificial Intelligence" Department at Almaty University of Power Engineering and Telecommunications named after G. Daukeyev, Almaty, Kazakhstan, E-mail: Beketova2111@gmail.com

Авторлар туралы мәлімет

Нагимов Алмас	Халықаралық Ақпараттық Технологиялар Университетінің ақпараттық жүйелер мамандығының 4-курс студенті Алматы қ., Қазақстан, E-mail: anm24012004@gmail.com
Бекетова Гулжанат Сакитжановна	PhD, «IT-инженерия және жасанды интеллект» кафедрасының доценті, Г. Дәукеев атындағы Алматы энергетика және байланыс университеті, Алматы, Қазақстан, E-mail: Beketova2111@gmail.com

Сведение об авторах

Нагимов Алмас	студент четвертого курса по специальности информационных систем Международного Университета Информационных технологии г. Алматы, Казахстан, E-mail: anm24012004@gmail.com
Бекетова Гулжанат Сакитжановна	PhD, Доцент кафедры «IT-инженерия и искусственный интеллект» Алматинского университета энергетики и связи имени Г.Дәукеева, г. Алматы, Казахстан, E-mail: Beketova2111@gmail.com