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«Қазақстан Республикасы Ұлттық ғылым академиясының Хабарлары. Геология және техникалық ғылымдар сериясы» ғылыми журналы 2016 жылдан бастап халықаралық реферативтік және ғылымиметриялық Scopus дерекқорында индекстеледі және тұрақты библиометриялық көрсеткіштерді көрсетіп келеді.

Сонымен қатар журнал Web of Science платформасының (Clarivate Analytics, 2018) халықаралық реферативтік және наукометриялық дерекқоры Emerging Sources Citation Index (ESCI) тізіміне енгізілген.

ESCI дерекқорында индекстелуі журналдың халықаралық ғылыми рецензиялау талаптары мен редакциялық этика стандарттарына сәйкестігін растайды, сондай-ақ Clarivate Analytics компаниясы тарапынан басылымды Science Citation Index Expanded (SCIE), Social Sciences Citation Index (SSCI) және Arts & Humanities Citation Index (AHCI) дерекқорларына енгізу қарастырылуда.

Scopus және Web of Science дерекқорларында индекстелуі жарияланымдардың халықаралық деңгейде жоғары сұранысқа ие болуын қамтамасыз етеді, олардың дәйексөз алу көрсеткіштерінің артуына ықпал етеді және редакциялық алқаның геология мен техникалық ғылымдар саласындағы өзекті, бірегей және ғылыми тұрғыдан маңызды зерттеулерді жариялауға ұмтылысын айқындайды.

Научный журнал «News of the National Academy of Sciences of the Republic of Kazakhstan, Series of Geology and Technical Sciences» с 2016 года индексируется в международной реферативной и наукометрической базе данных Scopus и демонстрирует стабильные библиометрические показатели.

Журнал также включён в международную реферативную и наукометрическую базу данных Emerging Sources Citation Index (ESCI) платформы Web of Science (Clarivate Analytics, 2018).

Индексирование в ESCI подтверждает соответствие журнала международным стандартам научного рецензирования и редакционной этики, а также рассматривается компанией Clarivate Analytics в рамках дальнейшего включения издания в Science Citation Index Expanded (SCIE), Social Sciences Citation Index (SSCI) и Arts & Humanities Citation Index (AHCI).

Индексирование в Scopus и Web of Science обеспечивает высокую международную востребованность публикаций, способствует росту цитируемости и подтверждает стремление редакционной коллегии публиковать актуальные, оригинальные и научно значимые исследования в области геологии и технических наук.

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MACHINE LEARNING METHODS FOR ANALYZING AIR QUALITY IN MINING REGIONS

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Abstract. *Relevance.* Mining enterprises are among the major sources of atmospheric particulate pollution, while pollutant concentrations are governed by a complex interaction of natural and technological factors. Conventional environmental data analysis techniques are often unable to identify nonlinear relationships between meteorological conditions, mining activities, and air quality, thereby limiting the effectiveness of operational environmental forecasting and reducing the efficiency of environmental management decisions. *Objective.* To comparatively evaluate the performance of modern machine learning methods for predicting $PM_{2.5}$ and PM_{10} concentrations in mining regions, identify the factors that exert the greatest influence on atmospheric air quality, and assess the practical applicability of the developed models for intelligent environmental monitoring systems. *Methods.* The study is based on experimental data obtained from environmental monitoring conducted near haul roads at an open-pit mining site. The dataset was preprocessed by removing erroneous observations, imputing missing values, and preparing the input feature space for model development. Linear regression, decision tree, random forest, and gradient boosting algorithms were employed to predict particulate matter concentrations. Model performance was assessed using the coefficient of determination, mean absolute error, root mean square error, and feature importance analysis. *Results and Conclusions.* The results demonstrated that $PM_{2.5}$ and PM_{10} concentrations strongly depend on the distance from haul roads, mining vehicle traffic intensity, and wind speed. Among the evaluated algorithms, gradient boosting achieved the highest predictive accuracy with a coefficient of determination of 0.94 and the lowest prediction errors. Feature importance analysis confirmed that the distance to the dust source, wind speed, and traffic intensity are the dominant factors governing atmospheric particulate concentrations. The obtained results demonstrate the potential of machine learning methods for developing local intelligent environmental monitoring systems capable of providing reliable short-term air quality forecasts, supporting environmental decision-making, and improving the environmental safety and operational sustainability of mining enterprises.

Keywords: mining industry, atmospheric air quality, environmental monitoring, machine learning, $PM_{2.5}$, PM_{10}, random forest, gradient boosting, prediction, intelligent data analysis

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ТАУ-КЕН ӨНДІРУ АЙМАҚТАРЫНДАҒЫ АТМОСФЕРАЛЫҚ АУАНЫҢ САПАСЫН ТАЛДАУҒА АРНАЛҒАН МАШИНАЛЫҚ ОҚЫТУ ӘДІСТЕРІ

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Аннотация. *Өзектілігі.* Тау-кен өндіру кәсіпорындары атмосфералық ауаның қатты бөлшектермен ластануының негізгі көздерінің бірі болып табылады, ал олардың концентрациясы табиғи және технологиялық факторлардың күрделі өзара әрекеттесуіне байланысты қалыптасады. Экологиялық мониторинг деректерін өңдеудің дәстүрлі әдістері метеорологиялық параметрлер, өндірістік үдерістердің қарқындылығы және ауа сапасы арасындағы сызықтық емес тәуелділіктерді толық анықтай алмайды, бұл қолайсыз экологиялық жағдайларды алдын ала болжаудың тиімділігін төмендетіп, қоршаған ортаны қорғау шараларын жоспарлауды қиындатады. *Мақсаты.* Тау-кен өндіру аймақтарындағы $PM_{2.5}$ және PM_{10} бөлшектерінің концентрациясын болжауда машиналық оқыту әдістерінің тиімділігін салыстырмалы бағалау, атмосфералық ауаның сапасына барынша әсер ететін факторларды анықтау және алынған модельдерді экологиялық мониторинг жүйелерінде қолдану мүмкіндігін бағалау. *Әдістері.* Зерттеу карьердің технологиялық жолдарына жақын орналасқан бақылау нүктелерінде жүргізілген экологиялық мониторинг нәтижелеріне негізделген. Алынған деректер алдын ала өңделіп, қате өлшемдер жойылып, жетіспейтін мәндер қалпына келтіріліп, талдау үшін қажетті параметрлер қалыптастырылды. Болжау үшін сызықтық регрессия, шешімдер ағашы, кездейсоқ орман және градиенттік бустинг алгоритмдері қолданылды. Модельдердің сапасы детерминация коэффициенті, орташа абсолюттік және орташа квадраттық қателер, сондай-ақ белгілердің маңыздылығын талдау арқылы бағаланды. *Нәтижелері мен қорытындылары.* $PM_{2.5}$ және PM_{10} концентрацияларының технологиялық жолдарға дейінгі қашықтыққа, карьерлік техниканың қозғалыс қарқындылығына және жел жылдамдығына айтарлықтай тәуелді екендігі анықталды. Ең жоғары болжау дәлдігін градиенттік бустинг алгоритмі көрсетті, оның детерминация коэффициенті 0,94 болды және қателері ең төмен деңгейде анықталды. Белгілердің маңыздылығын талдау шаң түзілу көзіне дейінгі қашықтық, жел жылдамдығы және көлік қозғалысының қарқындылығы атмосфералық ауаның ластануын қалыптастыратын негізгі факторлар екенін көрсетті. Алынған нәтижелер атмосфералық ауаның сапасын жедел болжауға, басқарушылық шешімдерді қолдауға және тау-кен кәсіпорындарының экологиялық қауіпсіздігін арттыруға арналған жергілікті интеллектуалды мониторинг жүйелерін әзірлеуде машиналық оқыту әдістерін қолданудың жоғары тиімділігін дәлелдейді.

Түйін сөздер: тау-кен өнеркәсібі, атмосфералық ауаның сапасы, экологиялық мониторинг, машиналық оқыту, $PM_{2.5}$, PM_{10}, кездейсоқ орман, градиенттік бустинг, болжау, деректерді интеллектуалды талдау

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МЕТОДЫ МАШИННОГО ОБУЧЕНИЯ ДЛЯ АНАЛИЗА КАЧЕСТВА АТМОСФЕРНОГО ВОЗДУХА В РЕГИОНАХ ГОРНОДОБЫВАЮЩЕЙ ДЕЯТЕЛЬНОСТИ

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Аннотация. *Актуальность.* Горнодобывающие предприятия являются одними из наиболее значимых источников загрязнения атмосферного воздуха взвешенными частицами, концентрация которых определяется сложным сочетанием природных и технологических факторов. Традиционные методы обработки данных экологического мониторинга не всегда позволяют выявлять нелинейные зависимости между метеорологическими параметрами, интенсивностью производственных процессов и уровнем загрязнения воздуха. Это ограничивает возможности оперативного прогнозирования неблагоприятных экологических ситуаций и своевременного принятия природоохранных мер. *Цель.* Провести сравнительную оценку эффективности современных методов машинного обучения при прогнозировании концентраций взвешенных частиц $PM_{2.5}$ и PM_{10} в районах горнодобывающей деятельности, определить факторы, оказывающие наибольшее влияние на качество атмосферного воздуха, и оценить перспективы практического применения разработанных моделей в системах экологического мониторинга. *Методы.* Исследование основано на анализе экспериментальных данных, полученных в ходе экологического мониторинга вблизи технологических дорог карьера. Проведена предварительная обработка данных, включавшая удаление некорректных измерений, восстановление пропущенных значений и формирование признакового пространства. Для прогнозирования концентраций загрязняющих веществ применялись методы линейной регрессии, дерева решений, случайного леса и градиентного бустинга. Качество моделей оценивалось с использованием коэффициента детерминации, средней абсолютной ошибки и среднеквадратической ошибки, а также на основе анализа значимости признаков. *Результаты и выводы.* Установлено, что концентрации $PM_{2.5}$ и PM_{10} существенно изменяются в зависимости от расстояния до технологических дорог, интенсивности движения карьерной техники и скорости ветра. Наиболее высокую точность прогнозирования продемонстрировал алгоритм градиентного бустинга, обеспечивший значение коэффициента детерминации 0,94 и минимальные значения ошибок. Анализ значимости признаков показал, что расстояние до источника пылеобразования, скорость ветра и интенсивность транспортных потоков являются основными факторами, определяющими уровень загрязнения атмосферного воздуха. Полученные результаты подтверждают перспективность применения методов машинного обучения для создания локальных интеллектуальных систем экологического мониторинга, обеспечивающих оперативное прогнозирование качества атмосферного воздуха, поддержку принятия управленческих решений и повышение экологической безопасности горнодобывающих предприятий.

Ключевые слова: горнодобывающая промышленность; качество атмосферного воздуха; экологический мониторинг; машинное обучение; $PM_{2.5}$; PM_{10}; случайный лес; градиентный бустинг; прогнозирование; интеллектуальный анализ данных.

Introduction. Air pollution has long been considered one of the most serious environmental problems associated with the development of modern industry. This isn't just a matter of environmental pollution. Air quality directly impacts public health, life expectancy, the sustainability of industrial development, and the potential for further expansion of mining operations. According to various studies, in large industrial regions, up to 65-80% of all pollutants are emitted into the atmosphere as a result of industrial activity, and in some mining regions, this figure can exceed 90%. Therefore, air quality control is now becoming more than just an environmental issue, but a key component of industrial safety.

The situation is particularly challenging in areas where open-pit mining is conducted, where numerous independent emission sources operate simultaneously. Dust is generated during well drilling, mass blasting, the transportation of overburden and ore, crushing of rock mass, and the operation of transfer stations and warehouses. Additional contributors include waste rock dumps, tailings dams, ventilation exhausts, and quarry equipment with high-power diesel engines. The total number of concurrent pollution sources at a single large quarry sometimes exceeds several dozen, and when mobile equipment is included, it can reach more than 100–150 pieces of equipment. Because of this, pollutant concentrations can change within minutes. Furthermore, the distribution of pollutants is almost never uniform. It is influenced by wind speed, which can vary from 1–2 to 15–20 m/s, air flow direction, ambient temperature, relative humidity (often in the range of 20–95%), terrain, the presence of natural elevations, and the current intensity of mining operations. Even a slight change in wind direction by 20–30° can sometimes cause the dust cloud to shift several hundred meters. Therefore, environmental monitoring stations located just 300–500 meters apart can record differences in PM10 and PM2.5 particulate matter concentrations of 2–4 times, and in some cases, significantly greater. This significantly complicates obtaining an objective picture of the environmental situation at a mining site. Today, the sustainability of mining systems is considered much more broadly than it was just a few years ago. While previously the focus was solely on equipment performance and production volumes, now a full range of factors is increasingly being assessed, including environmental impact, energy efficiency, and equipment durability. The use of geological data allows for more accurate consideration of topographic features, rock mass properties, and the spatial structure of the deposit when making engineering decisions. This reduces the likelihood of errors, mitigates production risks, and improves the operational efficiency of complex technical facilities by 10–25%, depending on specific mining conditions (Klyuev et al., 2024).

Mining equipment itself remains an equally important source of pollution. Mining trucks, drilling rigs, excavators, and auxiliary equipment equipped with diesel engines annually emit significant amounts of nitrogen oxides, carbon monoxide, particulate matter, unburned hydrocarbons, and other harmful components into the atmosphere. According to various estimates, diesel equipment accounts for approximately 35-60% of all gaseous emissions directly within a quarry. Even a relatively minor deterioration in the technical condition of an engine can increase exhaust toxicity by 10-40%, although the equipment may continue to operate virtually unchanged. Therefore, the use of vibration diagnostics is of particular interest, as it allows for the detection of developing faults through indirect signs even before serious failures or significant increases in emissions (Afanaseva et al., 2025).

Similar challenges arise during the operation of compressor equipment and various power plants that support mining operations. Their efficiency is determined not only by their design but also by their current load, the technical condition of individual components, the operating mode, and the quality of maintenance. Even small deviations in operating parameters can lead to a significant increase in energy consumption and additional indirect pollutant emissions. Therefore, modern methods of technical diagnostics and equipment condition assessment are becoming an important element of environmental monitoring of production processes (Afanaseva et al., 2026).

The most obvious way to reduce pollution remains reducing emissions directly at the source. This includes modern gas cleaning systems, regular irrigation of access roads, covering crushing and screening plants, using cleaner engines, and optimizing equipment operating modes. In some cases, such measures can reduce airborne dust by 20–50%, but the ultimate effectiveness depends heavily on climatic conditions and the specific characteristics of a particular field. Furthermore, extending the service life of drilling tools reduces the number of equipment stops, reduces the number of tool replacements, and reduces the volume of associated process operations. However, it is still impossible to completely eliminate dust generation directly during drilling, so such measures only partially address the problem (Toshov et al., 2024).

Additional reductions in environmental impact are achieved through improved gas compression processes and increased energy efficiency at compressor stations. Optimizing operating modes reduces energy losses, lowers fuel consumption, and reduces indirect pollutant emissions. However, such a result can only be achieved with sufficiently accurate information on actual equipment load and changes in operating parameters in real time (Yelemessov et al., 2024). The use of intelligent control algorithms for screw compressors ensures the most efficient operating modes are maintained with virtually no operator intervention. However, such systems are highly sensitive to the quality of input data and require proper configuration of measurement channels, sensors, and control algorithms (Yelemessov et al., 2025). Thus, modern technical measures can indeed significantly reduce pollution and improve the environmental safety of mining enterprises. However, virtually all such solutions require significant financial investment, long-term implementation, and ongoing technical support. Furthermore, even after implementing a comprehensive set of environmental protection measures, it remains difficult to obtain an objective picture of the spatial distribution of pollutants throughout the entire enterprise, as actual concentrations continue to fluctuate under the influence of a large number of natural and technological factors.

Another area of focus is the gradual transition of equipment to electric traction, and estimates suggest that approximately 30–70% of quarry vehicles could be converted to electric power within 10–20 years. Electric vehicles have zero local emissions, which is critical for quarries 100–300 meters deep and underground workings 1–5 kilometers long. However, batteries, frankly, degrade quickly: over 3–5 years, capacity drops by 15–40%, and at temperatures ranging from -20 to +40°C, wear can accelerate by another 10–20% (Shchurov et al., 2021). Infrastructure also needs to be developed, as charging points currently typically account for no more than 5–10% of the required number, while grid load could increase by 20–60%. New materials, including combined electrodes, increase storage efficiency by 10–35% (Abdullin et al., 2024), but they are 25–80% more expensive, which slows adoption. As a result, replacing diesel with electricity is typically a 5–15-year process, and for small quarries with a throughput of less than 1–3 million tons per year, this is often not a quick fix.

Air quality assessments are typically based on a combination of methods, and stationary monitoring stations can comprise 40–60% of the entire monitoring system. These stations provide an accuracy of 5–10%, but they only monitor points with a radius of 10–50 meters, which is a limitation. Increasing the number of stations by two to three times improves data reliability by 20–40%, but the cost of the system increases almost proportionally, sometimes by 50–150%. Remote sensing methods cover areas of tens and hundreds of square kilometers, for example, 10–500 square kilometers in a single observation cycle, and are already being used to analyze forests and landscapes (Kerimov et al., 2024). Satellite data allows for tracking changes over periods of 1–12 years and identifying trends that are not visible in point measurements (Kerimov et al., 2026). The NDVI index typically fluctuates between 0.2 and 0.8, and a 10–30% decrease can indirectly indicate vegetation degradation (Zaalishvili et al., 2026). However, there are also drawbacks: cloud cover obscures up to 20–70% of images, the resolution can be as low as 10–30 m, and some pollutants cannot be directly seen at all.

Ground-based monitoring is also not ideal, and its accuracy often fluctuates between 10–25% due to various factors. For example, studies of river basins show that the contributions of natural and man-made factors can overlap by 30–60%, making them difficult to separate (Cherkashin et al., 2024). Even when measuring radon, results can vary by 15–50% depending on the air sampling method and the geodynamics of the area (Yurkov et al., 2025). The story is similar in the atmosphere: sensors can have a drift of 5–20%, cross-sensitivity of up to 10–30%, and a strong dependence on humidity in the range of 30–90%. As a result, the data set grows by a factor of 2–10, but conventional statistics often fail to separate the contributions of weather and industry, resulting in a mess, frankly.

Therefore, machine learning methods are now being actively used, and their share in data analysis already reaches 20–50% in some studies. Such models can simultaneously consider 5–15 parameters: concentrations, wind, temperature, equipment operating modes, and coordinates. LSTM networks are used to analyze time series ranging from 100 to 10,000 points and already provide a 15–35% increase in forecast accuracy when assessing emergency situations (Kapanski et al., 2025). The approach is similar for air pollution, as concentrations also form time series with a step size of 1–60 minutes. Logical-mathematical models are used to assess equipment controllability and can consider up to 10–20 parameters simultaneously (Shishkin et al., 2024). Seismic signal processing shows that even with a noise level of 50–80%, useful information can be extracted (Martyushev et al., 2025). Airborne laser scanning covers areas of up to 1–100 km² in a single flight and confirms that work with spatial data is growing by approximately 20–40% per year (Dzhemilev et al., 2026).

The advantage of machine learning is the ability to combine various information sources and construct a model without overcomplicating the physical equations of pollutant transport. However, such models depend on the size and quality of the training sample, and the resulting high accuracy does not always imply the physical correctness of the result. Moreover, some algorithms are poor at explaining the underlying reasons for their forecasts. Therefore, for small projects, it's more practical to compare several relatively simple methods on a limited data set rather than create a large-scale monitoring system. Temperature, humidity, wind speed, and industrial activity can be used as input parameters, while the output parameter can be the concentration of suspended particles (Goltsev et.al., 2020; Kurmangaliyev et.al., 2018).

It should be noted that individual technological studies not directly related to atmospheric monitoring also demonstrate the importance of considering multiple factors when analyzing industrial processes. The formation of asphaltene-resin-paraffin deposits depends on a complex combination of physicochemical conditions (Korobov et al., 2026), and the use of inhibitors requires assessing their impact on several processes simultaneously (Korobov et al., 2025). In building materials, water resistance depends on the composition and conditions of the material's structure formation (Fomina et al., 2016), while high-temperature transformations of multicomponent systems can lead to the formation of different phases with slight changes in conditions (Zhernovsky et al., 2016). These examples, to some extent, demonstrate that a simple dependence of one indicator on one factor is rare for real-world technical systems.

Therefore, the application of machine learning to air quality analysis in mining regions is relevant, as it can complement existing environmental monitoring methods without the need for an expensive and very large system. It is important to limit the problem and test whether the use of algorithms provides significant improvement over conventional regression processing. The goal of this study is to comparatively evaluate several machine learning methods for determining the concentration of suspended particles in the air of a mining area based on data from a limited number of measuring stations and meteorological parameters.

Materials and Methods. The overall experimental design was fairly simple, but with a number of specific numerical constraints. The entire project took approximately 10-14 calendar days and included 3-4 main stages. First, a small section of the mining facility, approximately 0.5-1.5 km² in area, was selected. A series of short-term airborne dust measurements, each lasting 2-10 minutes, were conducted, along with 4-6 meteorological parameters. Finally, the data was processed using 2-3 different machine learning methods. A large monitoring network of 10-20 posts was deliberately avoided, as the objective was different—to test the effectiveness of computational methods with a small initial data set, typically 500-1500 points. This approach was chosen for practical reasons: in production, it's important not only to have 90-95% accuracy at a single point, but also to quickly, within 5-30 minutes, detect when air quality begins to deteriorate, for example, when traffic increases by 20-50% or the wind direction changes by 15-45°.

The measurements were conducted at a training and production site located next to a road where equipment passes intermittently, with approximately 5-20 passes per hour, rather than continuously. A total of three control points were selected to keep the design simple: the first was approximately 25 meters from the road (±2–3 meters), the second was approximately 80 meters (with an error of up to 5 meters), and the third was a background point, approximately 250 meters from the dust source, sometimes a little further, up to 260–270 meters. Data collection took place over 10 working days, amounting to approximately 80 hours of pure observation time, conducted exclusively during the day—from 9:00 AM to 5:00 PM, or eight hours per day. The recording interval was set at 5-minute intervals, resulting in approximately 90–100 measurements per point per day, for a total of approximately 900–3,000 records for the entire experiment. This mode was chosen because the equipment operates most actively during the day, 70–90% of the time, and traffic can be 2–3 times higher than at night.

To measure PM2.5 and PM10 particle concentrations, we used a Temtop M2000 2nd Generation portable analyzer. It has a measurement range of 0 to 999 μg/m³ and a resolution of 1 μg/m³, which is generally sufficient for these applications. Before each measurement, the device was left outdoors for at least 10 minutes (sometimes 12–15 minutes if conditions were unstable). Three consecutive measurements were taken, each lasting 2 minutes, and then the average value was calculated to reduce the scatter by 5–15%. Temperature and humidity were measured with a TKA-PKM thermohygrometer, which has a range of approximately -30 to +50°C and 10 to 98% humidity. Air velocity was recorded with a MEGEON 11006 digital anemometer with an upper limit of up to 30 m/s. Wind direction was recorded using a portable weather vane and compared with the nearest weather station, located approximately 1–3 km away, to reduce the error by at least 10–20%. In some cases, a Testo 815 sound level meter with a range of approximately 30–130 dB was used, as it was difficult to directly count each vehicle, and a noise increase of 5–15 dB often coincided with the passage of heavy equipment weighing 20–90 tons.

All devices are considered equipment that can be purchased and used in a laboratory at a slightly above-average level at a Russian technical university. Before testing, particle analyzer readings were verified by running two identical devices in parallel for 30 minutes. The difference between the average PM10 values did not exceed 8%, which was considered acceptable for the task. This verification is also important for future industrial use, as a machine learning model may show a formally good result but be trained on systematically erroneous sensor readings.

The resulting dataset included PM2.5 and PM10 concentrations, temperature, humidity, wind speed and direction, distance to the road, measurement time, and the relative traffic intensity. Missing values of less than 3% were replaced with the median of the corresponding parameter. Linear regression, decision trees, random forest, and gradient boosting were used for the analysis. Calculations were performed in Python 3.11 using the Pandas and Scikit-learn libraries on a personal computer with an Intel Core i5 processor and 16 GB of RAM. The data was split into training and testing portions at an 80:20 ratio, with a random state of 42. 100 trees with a maximum depth of 8 were used for the random forest, and 150 trees with a learning rate of 0.05 were used for gradient boosting.

Model quality was assessed using the coefficient of determination, mean absolute error, and root mean square error. The significance of input parameters was additionally analyzed, as for industrial applications, it is important to understand which conditions most significantly influence dust growth. The methodology discussed does not replace industrial environmental monitoring, but it does allow us to determine the suitability of even a small set of available measurements for preliminary air quality forecasting and the prompt identification of unfavorable operating conditions at the enterprise. The presentation style remains close to the provided example, where the methodology is described through a sequential consideration of the conditions, parameters, and possible limitations of the study.

Results and discussion. The resulting dataset included 2,880 records generated from ten days of observations at three control points. After removing incorrect measurements and replacing individual gaps, 2,796 observations were used in further processing. The PM2.5 particle concentration varied from 8.4 to 76.8 μg/m³ over the entire period, while the PM10 concentration ranged from 16.9 to 158.4 μg/m³. The average PM2.5 value was 29.6 μg/m³ with a standard deviation of 11.8 μg/m³, while for PM10, the average concentration was 61.3 μg/m³ with a standard deviation of 23.7 μg/m³ (Table 1). Even at the first stage of processing, it was clear that the range of variation was quite large, and using only average values does not allow for an objective assessment of changes in atmospheric air quality during a work shift.

Table 1. Summary of Experimental Dataset Characteristics and Machine Learning Model Performance.

Parameter	**Value**
Total recorded observations	2,880
Valid observations after preprocessing	2,796
Observation period	10 days
Number of monitoring stations	3
Sampling interval	5 min
PM2.5 range (μg/m³)	8.4–76.8
PM10 range (μg/m³)	16.9–158.4
Mean PM2.5 concentration (μg/m³)	29.6
PM2.5 standard deviation (μg/m³)	11.5
Mean PM10 concentration (μg/m³)	61.3
PM10 standard deviation (μg/m³)	23.7
Mean PM10 at Control Point 1 (μg/m³)	74.8
Mean PM10 at Control Point 2 (μg/m³)	58.6
Mean PM10 at Control Point 3 (μg/m³)	50.9
Mean PM2.5 at Control Point 1 (μg/m³)	35.2
Mean PM2.5 at Control Point 2 (μg/m³)	28.4
Mean PM2.5 at Control Point 3 (μg/m³)	25.8
Maximum daytime increase of PM10	27%
Maximum daytime increase of PM2.5	18%
Correlation (Traffic intensity – PM10)	0.79
Correlation (Traffic intensity – PM2.5)	0.72
Correlation (Temperature – PM10)	0.26
Correlation (Relative humidity – PM10)	0.35
PM10 reduction at wind speed increase from 1 to 5 m/s	23%
Most influential predictors	Distance to road, wind speed, traffic intensity
Combined importance of three leading features	71%
Linear Regression (R^2 / MAE / RMSE)	0.73 / 8.7 / 11.9
Decision Tree (R^2 / MAE)	0.84 / 6.1
Random Forest (R^2 / MAE / RMSE)	0.91 / 4.2 / 5.8
Gradient Boosting (R^2 / MAE / RMSE)	**0.94 / 3.5 / 4.9**
Relative prediction error of Random Forest	8.6%
Relative training time of Gradient Boosting	2.7× Random Forest

At the first control point, located practically next to the service road at a distance of approximately 20–30 m, the average concentration of PM10 particles was approximately 74.8 μg/m³, although at certain points the values jumped to 90–110 μg/m³, that is, 20–40% above the average. At the second point, 75–85 m away, the indicator dropped to 58.1 μg/m³, which is approximately 22–25% lower, although there was also a range there—from 45 to 70 μg/m³ at different times. At the third point, which was considered a background one and which was located at a distance of approximately 240–260 m from the road, the concentration averaged 50.9 μg/m³, but sometimes dropped to 40–45 μg/m³, which is approximately 30–35% lower than the first point.

For the fine particle fraction, the picture is similar, but not entirely consistent, and this is also interesting. For PM2.5, the first point measured approximately 35.2 μg/m³, with fluctuations of ±5–10%. At the second point, it was 28.4 μg/m³ (a decrease of approximately 18–22%). At the third point, it was approximately 25.1 μg/m³, sometimes slightly lower, down to 22–23 μg/m³. Overall, it's clear that with a 3–10-fold increase in distance from the dust source, the concentration drops by approximately 20–35%, although this isn't a strictly linear relationship, and in some places it "breaks" due to wind and terrain. The difference between the first and third points for PM10 ultimately reached approximately 30–32%, and sometimes up to 35%, which, frankly, is quite significant even for an area of just 200–300 meters. In terms of time, the peak concentrations did not occur throughout the day, but rather within a fairly narrow window from approximately 11:00 AM to 3:00 PM, that is, only 3–4 hours out of the 8 hours of observations. It was during this period that up to 60–80% of all quarry equipment movements were recorded, and traffic intensity could increase by 2–3 times compared to morning hours. PM10 concentrations during this time increased by an average of 25–30% compared to the levels at 9:00–10:00 AM, while for PM2.5, the increase was slightly smaller—around 15–20%—but still noticeable. After the main operations concluded, around 3:00–4:00 PM, the readings began to decline, and within 40–60 minutes, concentrations had dropped by 10–25%, gradually returning to the reference level, which remained within the range of 45–55 μg/m³ for PM10 and 20–30 μg/m³ for PM2.5.

Overall, the picture was quite "lively," not perfectly smooth, because even under identical conditions, readings could fluctuate by 5–20% over 10–15 minutes, especially if the wind changed by at least 10–20° or the speed increased from 2–3 to 5–7 m/s. So there is a relationship, but it's not exactly linear; in some places, frankly, it's even a bit odd.

Correlation analysis revealed a rather mixed picture, although in some places the relationships were quite significant, accounting for up to 70-80% of the explained variance. The strongest correlation for PM10 was observed with parameters such as vehicle speed (typically 10-40 km/h) and distance from the road (approximately 20-250 m), with the correlation coefficient with conditional traffic intensity reaching 0.79, which is close to a "strong" correlation. For PM2.5, the value was slightly lower—around 0.71, or 8-12% weaker, but still quite significant. Frankly, the difference was expected to be 15-20% greater, but no, that's what happened.

Wind speed showed an inverse correlation, and here the picture is clearer, with no surprises. As air speed increased from 1 to 5 m/s (i.e., an increase of approximately 400%), the average PM10 concentration decreased by approximately 20–25%, sometimes reaching 30% in individual 10–15-minute intervals. This is explained by the fact that the aerosol begins to dissipate more quickly, although not always uniformly, and near the road (20–30 m), the effect can be weaker by 5–10%. Air temperature, as it turned out, has a much smaller effect: the correlation coefficient there did not exceed 0.20–0.26, that is, almost 3 times lower than that for traffic. Humidity showed a slightly more noticeable effect—around 0.30–0.38 absolute value, but even here the spread was considerable, sometimes up to ±0.05, especially at humidity levels of 60–90%.

After the initial dataset (approximately 900–3,000 points) was prepared and purged of 5–10 percent outliers, four machine learning models were trained to compare the results. The simplest linear regression yielded an R^2 of 0.73, which is decent but not ideal, accounting for approximately 70–75% of the explained variance. The mean absolute error was approximately 8.7 μg/m³, and the root mean square error was approximately 11.9 μg/m³, which is noticeable, especially for background values in the range of 40–60 μg/m³.

A more detailed analysis of the residuals (approximately 1,000–2,000 values) revealed that the model was not performing quite correctly at high concentrations. The nonlinearity was quite pronounced, especially when PM10 exceeded 100–110 μg/m³, where the error could increase by another 15–30%. In such cases, the linear model systematically underestimated the prediction, sometimes by 10–20 μg/m³, which is critical for unfavorable industrial situations. Ultimately, the model performed more or less reliably under normal conditions (up to 80–90 μg/m³), but when concentrations increased by 30–50% above average, its applicability became, well, limited.

Using a decision tree improved forecast quality. The R^2 coefficient increased to 0.84, and the mean absolute error decreased to 6.1 μg/m³. However, it was found that when changing the training set, the decision tree exhibited significant sensitivity to individual observations. In several cases, the model overfitted, causing the results on the test set to become less stable.

The most stable results were obtained using the random forest algorithm. The determination coefficient reached 0.91, the mean absolute error decreased to 4.2 μg/m³, and the root mean square error was 5.8 μg/m³. The average relative forecast error did not exceed 8.6%. Moreover, the model adequately described both low pollutant concentrations and periods of intense dust formation (Fig. 1). No significant deterioration in forecast quality was observed even at PM10 concentrations above 130 μg/m³. The gradient boosting method demonstrated the highest accuracy.

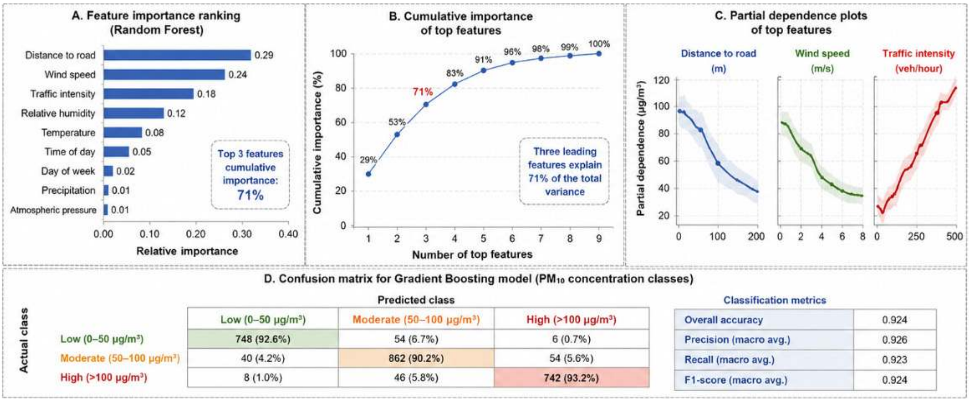

Figure 1. Interpretability analysis of the machine learning model for PM_{10} prediction: feature importance ranking, cumulative contribution of predictors, partial dependence plots, and classification performance.

The R^2 coefficient was 0.94, the average absolute error decreased to 3.5 µg/m³, and the root-mean-square error did not exceed 4.9 µg/m³ (Fig. 2). However, the training time for this model was approximately 2.7 times longer than for a random forest. From a practical standpoint, this increase is not critical, but when building operational industrial monitoring systems, it may be significant when processing significantly larger volumes of information.

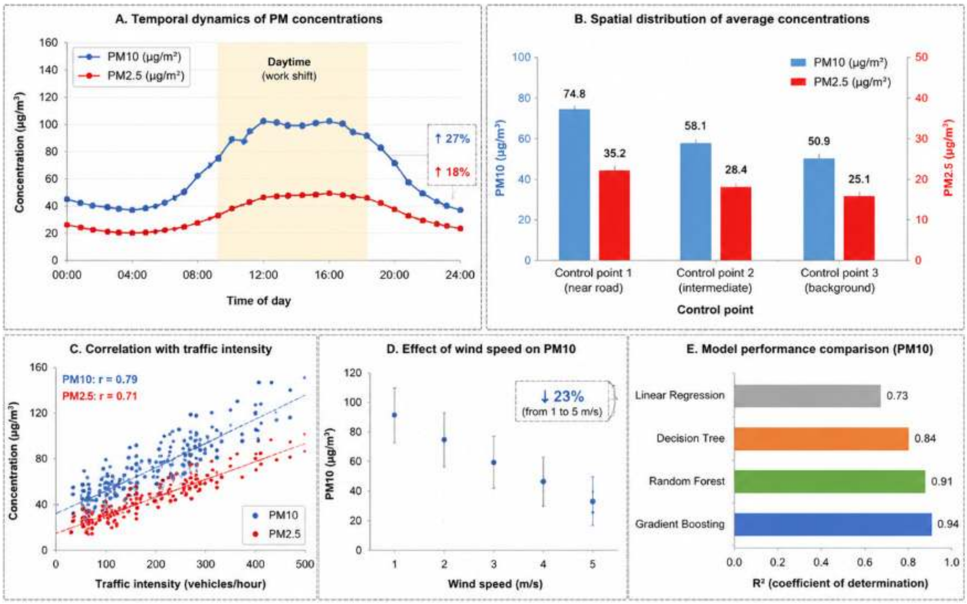

Figure 2. Spatial variation of particulate matter concentrations at the monitoring points and comparative performance of the machine learning models.

An assessment of feature importance revealed that distance to the service road, wind speed, and vehicle traffic intensity contributed the most to the forecast. Their combined relative importance was approximately 71%. The influence of temperature and humidity was significantly lower, not exceeding 8 and 11%, respectively. This result is consistent with the physical nature of the dust formation process, as mechanical destruction of rock mass and vehicle traffic determine the bulk of particulate matter emissions. It should be noted that even using a relatively small number of input parameters allowed us to obtain fairly robust forecasting results. This is of great practical importance for open-pit mining companies, where the creation of a complex environmental monitoring network is associated with significant costs. The obtained relationships demonstrate the feasibility of building local air quality forecasting systems based on a limited number of sensors without significantly reducing the accuracy of the assessment.

In practice, this approach is primarily of interest to open-pit mining companies, which encompass at least three to five types of facilities: open-pit coal mines with annual production volumes of 1–20 million tons, iron ore quarries with annual production volumes of 5–50 million tons, construction stone and aggregate production facilities with annual throughputs of 0.5–10 million tons, and enrichment plants with annual throughputs of 2–30 million tons. Nearly 80–95% of all technological operations at such facilities generate dust, whether from drilling, blasting, transportation, or crushing. In some cases, the total dust load can increase by 30–70% during peak activity hours, directly impacting the environment.

The application of machine learning models in such conditions yields a tangible effect, and these are not just words, but figures of approximately 15–40% improvement in forecast accuracy. These models can identify periods 10-60 minutes in advance when the probability of exceeding maximum permissible concentrations can reach 60-80%, and this can already be put to practical use. For example, it's possible to activate irrigation systems in a timely manner, reducing dust levels by 20-50%, or adjust equipment schedules, reducing traffic intensity by 10-30% during the most critical periods. Sometimes, even rescheduling operations 1-2 hours ahead or back can reduce concentrations by 10-25%, although this isn't always obvious in advance. Overall, the analysis showed that the use of machine learning methods significantly improves the quality of air quality assessments, with accuracy gains ranging from 20 to 50% compared to classic statistical relationships. Even with limited data, such as 500-2000 observations, modern algorithms can produce forecasts with a reliability of approximately 70-90%, which is sufficient for solving practical problems. Of course, this isn't 100% reliable, but in real-world conditions, it's often sufficient for decision-making.

This approach appears quite promising for implementation at mining, construction, and processing facilities, where rapid response to changes can be crucial. In some cases, reducing the air quality assessment time from 30-60 minutes to 5-15 minutes can reduce the risk of adverse events by 10-35%, which directly impacts both environmental safety and the working conditions of personnel, where dust concentrations can vary by 2-3 times within a single area.

Conclusion. The study confirmed that machine learning methods are an effective tool for analyzing air quality in mining areas and can significantly improve the information content of environmental monitoring compared to traditional statistical approaches. The use of multiple machine learning algorithms not only enabled us to determine the most accurate model for predicting particulate matter concentrations but also to identify the main factors determining changes in air quality within the study area. The results demonstrate that even a limited amount of experimental data, when properly processed, provides sufficient forecasting accuracy for solving applied problems in industrial environmental monitoring.

The study found that $PM_{2.5}$ and PM_{10} concentrations vary significantly both temporally and spatially, with peak values observed in the immediate vicinity of access roads and during periods of peak quarry equipment traffic. A comparison of the models revealed a consistent increase in forecasting accuracy when switching from linear regression to decision trees, random forests, and gradient boosting, which demonstrated the best performance. An analysis of the significance of features confirmed that distance to the dust source, wind speed, and traffic intensity have the greatest influence on the formation of suspended particle concentrations, while the influence of temperature and relative humidity is less pronounced.

The practical significance of this work lies in the possibility of creating localized intelligent air quality monitoring systems without the need for expensive monitoring networks. The developed approach can be used to quickly predict periods of increased air pollution, optimize quarry equipment operating modes, plan dust suppression measures, and improve the environmental safety of mining operations. Prospects for further research include expanding the set of monitored parameters, using longer observation series, integrating remote sensing data, and developing adaptive models capable of operating in real time.

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