This study considers the task to design a data analysis platform with predictive capabilities of neural networks. The object of research is intelligent decision-making systems built on deep learning methods. The proposed intelligent platform takes into account the specificity of working with data in the dynamic and uncertain environment of the pharmaceutical market. Its main purpose is the processing of various data formats, such as time series, regression, classification data sets to create forecasts based on various indicators. At the core of the platform architecture, along with technologies for backend and frontend development (HTML, JS, CSS, C#, .NET), MSSQL Server and TSQL for database management, are AI Microservices (Python, Flask); they are responsible for artificial intelligence services, in particular neural networks.

In order to identify the optimal model, which is able to effectively solve regression problems based on the selected indicators, the study analyzed several configurations of neural networks on End-to-end machine learning platforms. Distinctive features of the architecture of the designed data analysis platform include its ability to dynamically switch between different machine learning models based on predefined indicators and criteria such as prediction accuracy and model selection.

Improved interpretation of forecasts through the use of Explainable AI enables effective decision-making in the pharmaceutical industry. The functioning of the proposed instrumental decision-making base is demonstrated on the examples of forecasting trends in the consumption of pharmaceuticals by different groups in the pharmaceutical markets of different countries. Automating the model selection and prediction loss minimization process in a comprehensive data analysis platform (CDAP) improves forecast accuracy by approximately 15 % compared to traditional manually selected models

Keywords: deep learning, artificial neural networks, pharmaceutical market, data analysis, predictive tasks

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DESIGN OF AN INTELLIGENT DATA ANALYSIS PLATFORM FOR PHARMACEUTICAL FORECASTS

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1. Introduction

The pharmaceutical industry occupies a prominent place in the economy of any country in the world. The role of pharmaceuticals grows significantly under crisis conditions associated with epidemics, natural disasters, military conflicts, etc.

A structural feature of the pharmaceutical market is the presence of the vast majority of generic pharmaceutical products, which causes a high degree of competition between their manufacturers. Permanent development and monitoring of optimal development strategies are necessary to ensure competitive positions of pharmaceutical enterprises at various levels of management. The processes of forming such strategies are significantly complicated against the background of modern challenges of the pandemic, war, and various poorly predicted destabilizing factors. This makes them complex and multi-criteria.

In modern realities, the main destabilizing factors of the market environment include the following:

– significant (often difficult to predict) changes in the market situation caused by the variability of the demand structure as a result of the pandemic and the challenges of war: in particular, population migration, a significant decrease in solvent demand, etc. In general, all this increases the level of entropy of the pharmaceutical sector;

– strong price trends. Drug prices are rising at a high rate. The main reasons for this trend are inflation, an increase in the cost of raw materials (in particular, due to difficulties in logistics), and distribution costs. Thus, according to experts' estimates, the average price per package of the drug increased by 36 % in 2023 (Proxima Research, 2024) [1];

– the crisis state of the economic and political situation in the country. This is due to the specificity of the pharmaceutical industry: the strictest (unlike other sectors of the economy) regulation and control by government bodies. Therefore, the development of pharmaceuticals directly depends on the economic and political stability within the country. Many of the factors causing the state of crisis are mostly derived from the war: the general indicators of the economy are deteriorating, the rates of inflation are growing significantly, and there is a significant decline in direct foreign investment in the country;

– change in key aspects of the competitive environment of the pharmaceutical market as a result of globalization.

The war proved the importance of the pharmaceutical industry as one of the guarantees of national security and became a new challenge for domestic pharmaceutical companies. Ensuring the stable operation of the pharmaceutical industry has become one of the important tasks.

There is a reciprocal relationship between the transformations taking place in the pharmaceutical industry and the trends of the pharmaceutical market both in the domestic (local) and in the global format. As a complex system, the pharmaceutical market is characterized by a high degree of uncertainty, which is deepened by numerous crisis phenomena, force majeure circumstances, structural shifts, etc. In turn, this requires constant improvement of decision-making support systems at all levels of pharmacy management using not only traditional management methods and approaches but also a more flexible mathematical apparatus.

The actual direction of application of modern tools in this field is the development of intelligent decision support systems involving machine and deep learning methods based on artificial neural networks [2]. Although the ideas of machine and deep learning have a long history dating back to the 1940s, a significant breakthrough in the application of these techniques has only occurred in recent decades. The ability to process a large amount of diverse information, the creation of powerful learning algorithms contributed to the rapid development of these approaches. The differences in approaches are clearly defined in many literary sources, for example in [3]. In a generalized form, they refer to the following main characteristics: model architecture; use of data; work with attributes; training; data processing; productivity; interpretability of directions of use. A specific approach is chosen depending on the goals; requirements of the tasks being solved and available data. Both machine learning and deep learning have documented use cases where one technology outperforms the other. The latter testifies to the need for careful formulation and analysis of the tasks to be solved.

In the pharmaceutical industry, both approaches have found a certain spread due to compliance with the tasks that appear in the management contour of various production and sales links of the general system of the pharmaceutical industry.

One of the main tasks for the formation of market strategies of pharmaceutical companies is the task of forecasting market demand and sales of various types of pharmaceutical products, which is always a difficult process in a business environment with a high level of competition. Demand forecasting in the pharmaceutical industry has an even more complicated structure compared to other industries due to its connection with the health care sector, which requires taking into account the human factor, the spread of seasonal and epidemic diseases, sales conditions, the market share of competitive products, etc.

Thus, the growing complexity and instability of the pharmaceutical market, in particular under the conditions of economic and political crises, directly affect the processes of managerial decision-making at all levels of management of the pharmaceutical industry. This requires increasing the prognostic capabilities of decision support systems (DSSs) for a variety of time perspectives (from operational to strategic forecasts); makes relevant requirements for their architecture, model, and information base. The construction of DSS using various models of machine and deep learning on advanced platforms of complex data analysis is an actual area of research in the field of implementation of pharmaceutical forecasts.

2. Literature review and problem statement

Solving the problems of designing intelligent decision support systems using machine and deep learning methods attracts the attention of many researchers, which is reflected in a wide range of literary sources.

Work [4] emphasizes the importance of integrating various methods of deep learning in the field of interdisciplinary research. The importance of predictive data obtained on the basis of the use of neural networks in the formation of effective solutions is emphasized. The conclusions of the above interdisciplinary review regarding the influence of deep learning on the effectiveness of decision support systems (DSSs) are confirmed by the analysis of a significant range of works published in the time range of 2017–2022. At the same time, the analytical conclusions lack the disclosure of issues related to the provision of interpretability, generalization, and integration of the instrumental base to increase the reliability of DSS.

Although deep learning models have become more complex and powerful, their black-box nature remains a significant limitation, especially in decision-making processes where transparency and interpretability are critical. Additionally, current generative models and deep reinforcement learning (RL) systems, while innovative, often fail to provide clear interpretable rationales for the decisions or predictions they make.

Work [5] considers overcoming the issues of interpretability of forecast results, as well as the correlation of forecast accuracy in the case of using complex forecasting tools – such as ensemble models or deep learning (DL) models. The authors see a solution to the problem in the proposed unified system of interpreting SHAP forecasts (SHapley Additive exPlanations). However, the feasibility of using specific integrated assessment methods for specific types of models remains unresolved. The existing approach lacks a unified and consistent method for interpreting the predictions of complex models, especially in scenarios where accuracy is achieved at the expense of interpretability. Although various methods of interpretation have been proposed, the lack of a standardized approach makes it difficult to determine when one method is superior to another, especially in applications that require both high precision and clear interpretation.

Work [6] considers the integration of machine learning methods and multi-criteria decision-making (MCDM) methods. The authors conducted an analysis of a wide range of modern research methods that create an instrumental base of intelligent decision-making support systems with the determination of the fields of their further use. The basis of the conclusions was the analysis of a wide range of literary sources on the problem for the period from 2015 to 2020. But the main areas of analysis were the areas of use of decision support systems, as well as algorithms, methods, and techniques used in their construction. It seems that the presented material can be useful in the development of effective multi-criteria decision-making models, as well as the application of various integrated solutions in the construction of decision support systems (DSSs).

Methodological problems of the development of intelligent systems are raised in [7, 8], in which a broad overview of modeling directions involving various methods of artificial intelligence is provided. The authors emphasize the principles and capabilities of artificial intelligence methods as a basis for developing decision-making systems. At the same time, those works do not specify the data analysis tools used in the construction of the considered intelligent systems.

There is a certain class of works that tackle basic methodological problems of machine and deep learning, as well as promising directions for the development of this instrumental field. Examples include the fundamental reviews reported in [9–13].

In [9, 10], the basic architecture of machine learning (artificial neural network – multilayer perceptron (MLP)) is discussed in detail. The deep learning paradigm is widely used in the design of intelligent decision support systems. A significant number of applications using deep learning (DL) methods appear in various fields of activity. The advantage of DL is the broad possibilities of analyzing large volumes of data, which makes it possible to significantly expand the boundaries of traditional research tasks. Accordingly, the Deep Learning methodology is developed, which is determined by a number of works on this issue.

From the point of view of the generalization of existing DL methodology and the prospects for its development, work [11] is of interest, in which the authors focus on the most important aspects of DL and on the latest developments included in this area. In particular, the paper presents the types of DL techniques and networks, the development of network architecture, considered convolutional neural networks. The authors also emphasized the existing problems and prospects for the further development of the Deep Learning methodology.

A possible solution to overcome the existing problems of Deep Learning is the generalization and development of DL methodology, which is carried out in [12], in which an effective approach to the definition of deep neural networks is developed. The book thoroughly examines the learning mechanisms of deep networks, in particular learning mechanisms for nonlinear models. The authors prove that the complexity of the network model is determined by the ratio of depth and width, and the use of information-theoretic methods makes it possible to evaluate their optimal ratio from the point of view of the effectiveness of applied implementation.

A generalization of the methodological foundations of machine learning and deep learning is also formulated in [13]. It is shown that the positive points are a clear conceptual definition of the terminological base and, on this basis, the process of building automated analytical models using machine and deep learning methods. There is also interest in raising the applied aspects of the problem, namely, an overview of the possibilities of implementing specific applications of intelligent systems in various spheres of activity. However, the indicated areas of possible implementation are limited only to the realm of electronic markets and network business.

Along with deepening the methodology of creating intelligent decision support systems, the spectrum of their applied applications is expanding significantly. Pharmaceuticals is one of the industries where decision support systems (DSSs) find successful use.

One of the key aspects of the activity of pharmaceutical companies to ensure their stable position on the market is forecasting the demand for pharmaceutical products, which, due to its complex structure, requires the involvement of a flexible and diverse instrumental base. At the current stage, there is a certain range of applied applications for solving this problem, in particular, using the methodology of deep learning and neural networks. However, in the end, the problem cannot be considered solved precisely due to the need to take into account a huge number of factors influencing demand, which are of a diverse nature and differ for different nomenclature groups of products, segments of the pharmaceutical market, and potential users. Thus, a number of studies [2, 14, 15] experimentally prove that for different categories of drugs (according to available data), the prognostic capabilities of various applied models differ, that is, there is no single optimal demand forecasting model. At the same time, the breadth of coverage of the problem, the goals, and necessary accuracy of specific forecasts and, of course, the available information support for forecast calculations are important.

From this point of view, work [2] is of interest, in which the methods of surface and deep neural networks used for demand forecasting are considered. The authors considered the validation of various methods in order to expedient their use in determining sales and marketing strategies.

Work [14] also considers demand forecasting in the pharmaceutical industry using a neuro-fuzzy approach. The neuro-fuzzy approach is used in the course of forecasting sales volumes, taking into account the influence of external factors – the human factor, seasonal and epidemic diseases, the market share of specific types of products, sales conditions. The authors prove the effectiveness of using the given approach under specific circumstances. But due to the limited ability of the neuro-fuzzy approach to process complex data, this can generally be considered a significant disadvantage compared to deep learning in prediction tasks.

Work [15] focuses on solving the problems of drug prediction using deep learning methods. Staged tasks are considered from the point of view of the need to forecast the actual needs for medicinal products of specific segments of the pharmaceutical market. It is important to avoid problems with preservation and spoilage of drugs, and on the other hand, to achieve complete satisfaction of customer needs. The authors prove the feasibility of using machine and deep learning methods to solve this class of problems. In general, the paper proves that the predictive capabilities of the selected mathematical apparatus ensure the optimization of the inventory level, which reduces costs and increases subsequent sales. However, the forecasts did not take into account the influence of factors that determine the appropriate volumes of available drugs in individual links of the supply chain. In addition (as pointed out by the authors themselves), it is advisable to increase the range of input data to ensure the use of more flexible deep learning algorithms with further determination of the error rate for each of the algorithms. According to this, it will be possible to determine the best model based on the accuracy of forecasts.

The above review of the literature proves the positive results of using machine and deep learning methods, in particular, in the processes of analysis and forecasting in various subject areas. However, the main drawback of existing approaches is the lack of flexibility and adaptability needed to handle various data types and formats (such as time series, raw data, and API-integrated data) when applying predictive models. Although neural network algorithms are effective in producing accurate predictions, they often do not take into account the varying nature of the input data or the need to select the most interpretable model for each unique scenario. This limitation makes it difficult to generalize the results to different contexts or data types.

Increasing the effectiveness of forecasts using the given apparatus creates the need to involve special complex platforms for data analysis and the selection of models most suitable for their processing.

3. The aim and objectives of the study

The aim of our study is to design a complex data analysis platform, which includes a decision support system based on a neural network, designed to work effectively in a dynamic and uncertain environment of the pharmaceutical market. This will make it possible to take into account the forecast trends of pharmaceutical markets.

To achieve the goal, the following tasks are set:

– to design the architecture of a complex platform for intelligent data analysis, aimed at processing various data formats in order to form forecasts based on various indicators;

– to choose a neural network for solving forecasting problems on the CDAP platform;

– to test the proposed platform by applying it to predict trends in the consumption of pharmaceuticals, trends in the consumption of pharmaceuticals in different product categories in different pharmaceutical markets.

4. The study materials and methods

The object of our research is intelligent decision support systems designed for forecasting trends in pharmaceutical markets and built on the basis of deep learning and artificial neural networks.

The research hypothesis assumes that the use of predictive data on the consumption of pharmaceuticals obtained with the help of an intelligent platform could provide more accurate and effective forecasts of trends in the pharmaceutical markets compared to conventional methods, which would contribute to increasing the efficiency of the regulatory functions of health care institutions.

Assumptions adopted in the study are as follows:

– the data used for training neural networks are complete and correct;

– selected deep learning algorithms are suitable for analysis and forecasting within pharmaceutical markets.

Using historical data on pharmaceutical consumption can help predict future trends. The inaccuracy of data, periods of seasonal fluctuations, the possibility of obtaining up-to-date information that is not always available negatively affect the accuracy of forecasts. In this regard, there are references in a number of works by researchers working in the field of health care and pharmacology. As an example, we can cite works [15, 16].

In Ukrainian realities, the problem is even more complicated. In terms of the pharmaceutical market of Ukraine, the main sources of data are the following:

– information from the consulting company engaged in analytical research of the pharmaceutical market Proxima Research (2024) [1]. But the information is not publicly available and is not always suitable for making accurate predictions (the necessary data are missing; historical data sets cover short periods, i.e., the sample is not representative; the data is outdated, etc.);

– information from the weekly publication “Apteka” and the E-commerce website: the data are not always complete, often refer to limited branches of the pharmaceutical industry and the pharmaceutical market (Official website of Weekly Pharmacy, Official website of E-commerce) [17, 18];

– information from the reporting of pharmaceutical companies: “JSC pharmaceutical firm “DARNYTSYA”, “FARMAK” [19, 20].

However, all of these sources are objectively limited or completely unavailable under martial law due to existing prohibitions on the disclosure of information related to the industry working for the defense of the country.

The above creates objective conditions for realizing the possibilities of more flexible work with data, implementation of a developed model base, use of model complexes, comparative analysis, etc.

Accordingly, the development of a comprehensive data analysis platform (Comprehensive data analysis platform – CDAP) is proposed. The main task of a complex data analysis platform is to process various data formats to create forecasts based on various indicators, such as time series, regression, classification data sets, and others. The complex platform will solve data analysis tasks using special algorithms developed for each format.

The following technologies are used in the CDAP architecture: HTML, JS, CSS – for the development of the front-end of the platform; C#, .NET – for the development of Backend and server logic; AI Microservice (Python, Flask) – for artificial intelligence services, in particular neural networks; MSSQL Server, TSQL, Windows – for managing and storing databases.

To determine the effective neural network model that will be used on the CDAP platform, a comprehensive set of tools provided by the machine learning platform (End-to-end machine learning platforms, 2023; 2024) [21] was used.

To build and train neural networks, the study used the TensorFlow open source machine learning library developed by Google [22].

The flexibility of CDAP in adapting to different data formats, as well as the use of Explainable AI (XAI) methods, allowed us not only to achieve high accuracy but also to ensure transparency in the process of model selection and decision-making.

5. Results of designing a data analysis platform for pharmaceutical forecasts

5. 1. Architecture of the CDAP platform

In the field of data analytics platforms, the architecture ensures efficiency, scalability, and security. Standard practice is to implement REST (Representational State Transfer) API and JWT (JSON Web Token) used for API (Application Programming Interface) authentication. It is an open standard for generating access tokens, based on the JSON (JavaScript Object Notation) format. Integrating message queues such as (messaging system) or Kafka (data streaming platform) is also a widespread practice. However, these technologies create certain problems. The main challenges relate to ensuring data format independence. It is also important to ensure the flexibility of algorithms. Effective integration of large language models (LLMs) for automatic decision making is also important. The proposed approach focuses on these elements and aims to eliminate the shortcomings of conventional systems.

The architecture of the designed CDAP platform is shown in Fig. 1.

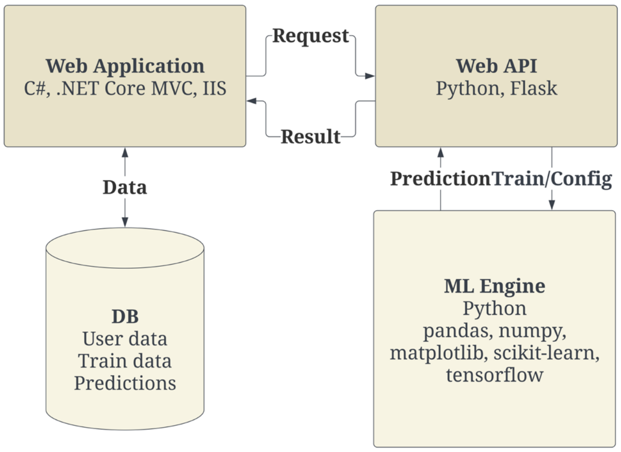

Fig. 1. CDAP platform architecture for neural network

The basis of CDAP's intelligent system is based on the integration between a user-oriented .NET Core MVC web application and the Flask Python web server and is designed to process and analyze pharmaceutical sales data. This opens up new opportunities for forecasting using:

– capabilities of the .NET Core MVC framework, as well as its compatibility between different OS (operating systems). The problem of compatibility, as described in works [23, 24], is a debatable issue when using conventional models;

– Python statistical libraries. Libraries like TensorFlow, Scikit-Learn help simplify the initial development. However, to meet the specific requirements of the CDAP platform, the standard TensorFlow architectures have been modified by adding custom layers and activation functionality.

The CDAP architecture is designed to overcome the limitations of conventional data analysis systems. It offers three key advantages: integration of different data formats, dynamic algorithmic adjustments based on the nature of the data, and improved interpretation of the obtained forecasts owing to Explainable AI (XAI). This architecture, in comparison with existing models, allows more flexible and accurate data analysis. This is achieved by automatically switching between multiple machine learning models based on predefined criteria such as prediction accuracy and loss. This dynamic machine learning model selection process distinguishes CDAP from conventional systems that often require manual intervention to select the appropriate model for certain data formats. An adaptive selection of models, including XGBoost, RandomForest, and neural networks, enables the platform to handle raw and categorical data as well as time series.

Unlike methodologies that focus on a single model or require manual configuration to work with different data formats, CDAP automatically evaluates and selects the optimal model for each scenario. For example, while other systems are optimized only for time series analysis or raw data processing, the CDAP platform dynamically analyzes these formats, choosing the best model based on the characteristics of each data set [5, 16].

The platform incorporates advanced interpretive artificial intelligence (XAI) techniques to provide a clear and transparent understanding of the decision-making process. Existing platforms often lack a sufficient level of transparency, which leads to problems in trust and acceptance, especially in industries where decision-making must be supported by a clear rationale [4, 5].

One of the key differentiators of CDAP is its ability to continuously monitor and adjust the selected model as new data becomes available or performance metrics change. For example, in scenarios where prediction accuracy starts to decline, the platform can automatically re-evaluate the available models, switch to a more appropriate one, or even adjust the parameters of the current model to better fit the changing data landscape. This adaptability is critical to maintaining a high level of predictive performance over time, especially in rapidly changing markets such as pharmaceuticals [5, 16].

Conventional platforms often struggle to work effectively with different data formats, limiting their ability to process and analyze diverse data sets. This rigidity hinders the ease of use of such platforms in different domains or data types, as noted in [25], highlighting the challenges of adapting analytical platforms to diverse data formats.

Providing a dynamic database structure facilitates rapid updates and scalability. This is a necessary improvement of conventional models with their static configuration of databases, which is defined in a certain range of works, among which, for example, [26].

Unlike traditional models that rely on a static set of algorithms, the CDAP platform offers the unique ability to change and select algorithms based on the analysis task at hand. This capability is facilitated by a modular design that allows researchers to connect different analytical modules as needed. This increases the versatility and efficiency of the platform in hypothesis testing, which meets the requirements set forth in [12].

The proposed platform is distinguished by the fact that it integrates LLM not only as tools for data interpretation but also as active components of the decision-making process. This integration uses the LLM's cognitive capabilities to analyze the results, generate insights and even recommend solutions. This improves the state of automatic decision-making systems beyond the current implementations defined in [12].

CDAP has a reliable and convenient interface, a secure backend, and uses AI microservices:

– artificial intelligence for machine learning (ML – Machine Learning);

– large language models (LLM – Large Language Model);

– reliable solutions for storing databases (DB – Database).

The architecture and capabilities of the CDAP platform go beyond conventional approaches to data analysis, offering a dynamic, integrated solution for automating decision-making processes. Unlike the general-purpose platforms described, for example, in [3, 27, 28], which primarily focus on certain types of data analysis, this system uses a wider range of data types with special analytical algorithms developed for each format. Thus, CDAP is designed to facilitate end-to-end processing, from data loading to forecast output.

The platform architecture consists of the following key components:

– user interface (HTML, JS, CSS) for interacting with the platform, including access to the dashboard, configuration options, and visualization of results;

– back-end (C#, .NET) that manages authentication, configuration saving, and communication with artificial intelligence microservices and database storage (DB);

– AI Microservice (Python, Flask) to perform ML (Machine Learning), NN (Neural Networks), and LLM (Large Language Model) tasks, handling model configurations, data processing, and forecast generation;

– MSSQL Server, TSQL, Windows to store user configurations, model parameters, and prediction results, ensuring data integrity and availability.

Fig. 2 shows the Sequence Diagram of user steps on the CDAP platform.

The diagram provides a visual representation of how an intelligent system works, highlighting important steps such as authentication, configuration management, and the prediction process. Let's briefly consider the essence of the above stages.

Authentication (*Authentication*). The user initiates an authentication request through the interface by entering their username and password.

Configuration management. Authenticated users access the configuration page to manage model configurations and set parameters for predictions. Configurations and CSV data are validated and stored in a DB repository (database) with parameter settings for future predictions.

Information panel and forecast (Dashboard). The dashboard allows users to select a model for forecasting using previously defined configurations and parameters. The AI (Artificial intelligence) microservice collects the necessary data and model parameters, performing prediction tasks. The results are displayed in a dashboard with the ability to use LLM (Large Language Model) responses for improved decision support.

Key system actions and responses.

Model selection and forecasting. Users select a model in the dashboard, triggering an AI microservice to retrieve the appropriate model configurations and initiate the prediction process. The microservice collects data and parameters, generates predictions, and sends the results back to the interface for display.

Downloading data and verifying the configuration. Users upload CSV data through the configuration page, where the system checks the file format and data integrity before saving to storage. Configurations associated with loaded data and selected models are set and tested, ensuring accurate forecasting settings. The independence of the data format and the flexibility in the configuration of the algorithms make it possible to quickly test hypotheses and compare the results. LLM (Large Language Model) integration adds a layer of intelligent decision support that sets it apart from conventional analytics tools.

Synergistic technological integration.

The innovation of the CDAP platform architecture is to strategically combine the computing power of Python with the robustness of the .NET web development framework; a combination that has hardly been explored in existing frameworks. Although current literature [21–24, 29] already highlights the capabilities of Python for analytics and .NET for web development, this platform combines these technologies to create a seamless end-to-end workflow. This integration facilitates not only data processing but also complex analytical operations and the generation of visual results.

Ability to adapt the data format. The ability of the platform to adapt to different data formats distinguishes it from more rigidly defined systems studied in [7], demonstrates its versatility. Existing models often limit the scope of application to certain types of data analysis (for example, time series or regression), not taking into account the multifaceted needs of modern data analytics. In contrast, the presented system is designed with built-in flexibility to process and analyze a wide range of data types, providing comprehensive analytical capabilities for a variety of business scenarios.

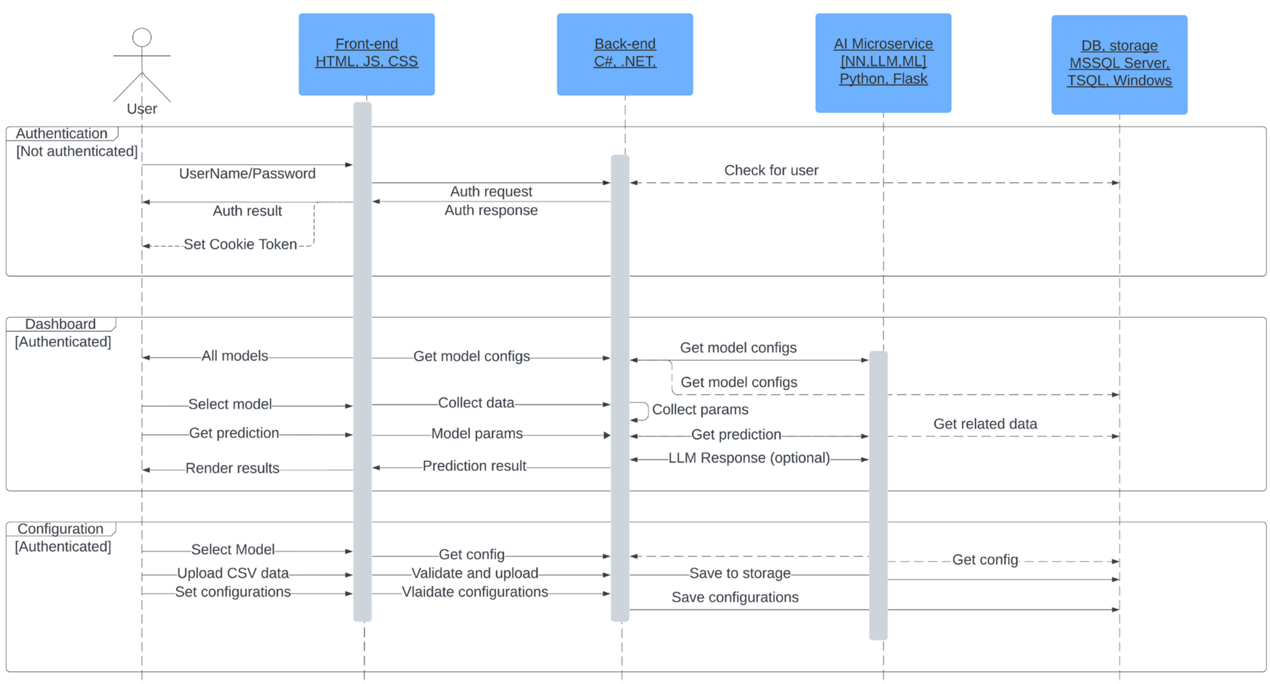

Fig. 2. Sequence Diagram of user steps in the CDAP platform

Security and Compliance. Security is another dimension in which the CDAP platform exceeds current industry standards, particularly those defined in [30, 31]. While most platforms address security issues separately, this approach integrates security measures directly into the development lifecycle, ensuring GDPR (General Data Protection Regulation) and OWASP (Open Web Application Security Project) compliance from the start.

Decision Making with LLMs. The inclusion of large language models (LLMs) for decision support is a distinctive feature that distinguishes the CDAP platform from those described in [12]. CDAP uses LLMs not only for interpretation but also to guide users in selecting the most appropriate models based on input data analysis.

Algorithm selection and justification. The CDAP platform evaluates models based on accuracy and efficiency, as well as their interpretability and adaptability to specific data types. This multifaceted evaluation system ensures the selection of the optimal model for each data set, which represents a significant departure from the more conventional methodologies common in the cited works.

5. 2. Selection of a neural network for solving forecasting problems on the CDAP platform

Selection of the activation function. To optimize the performance of the neural network, the activation function for each neural layer is initially set to the hyperbolic tangent (*tanh*) function. The training process includes 153 epochs with a learning rate of 0.03, intentionally omitting regularization to assess the raw predictive power of the model structure. Subsequent iterations explore the sigmoid function as an alternative, evaluating its impact on the network's ability to converge and generalize. A comparison between the *tanh* and *sigmoid* functions illustrates the trade-offs in the choice of activation functions, balancing computational efficiency and model accuracy.

Learning process. The training regime is carefully designed to gradually improve the parameters of the model. Without regularization, the focus shifts to learning rate and number of epochs as the main levers to control overfitting. Iterative adjustment of the activation function – from *tanh* to *sigmoid* – serves as a methodological study of how different nonlinearities affect learning dynamics and forecast accuracy.

Justification of model selection. Given the variety of pharmaceutical demand models, the system architecture must support the dynamic selection of predictive models based on the specific forecasting task. This flexibility is achieved owing to an algorithmic structure that evaluates several criteria:

– historical data characteristics: deviations and trends in historical demand data guide initial model selection.

– computing limitations: available computing resources affect the complexity;

– forecasting horizon: the desired forecasting range (short-term or long-term) affects the choice of model.

This structured approach to model selection ensures that the forecasting system is tailored and optimized for the task at hand, providing a strong foundation for developing effective demand forecasts.

Illustrative neural diagrams. In order to identify the optimal model, which is able to effectively solve regression problems based on the selected indicators, the study analyzed several configurations of neural networks on End-to-end machine learning platforms [21]. The TensorFlow library [22] was used to build and train the models.

Neural diagrams that visualize the architecture of a neural network with six and two hidden layers of neurons and the flow of data through it are shown in Fig. 3, 4.

The activation function *tahn* (tangential function) was chosen for each layer of neurons and the following parameters were set: the number of epochs (cycles) of learning – 153, learning rate (the rate of change of weights of the neural network during the learning process) – 0.03, no regularization.

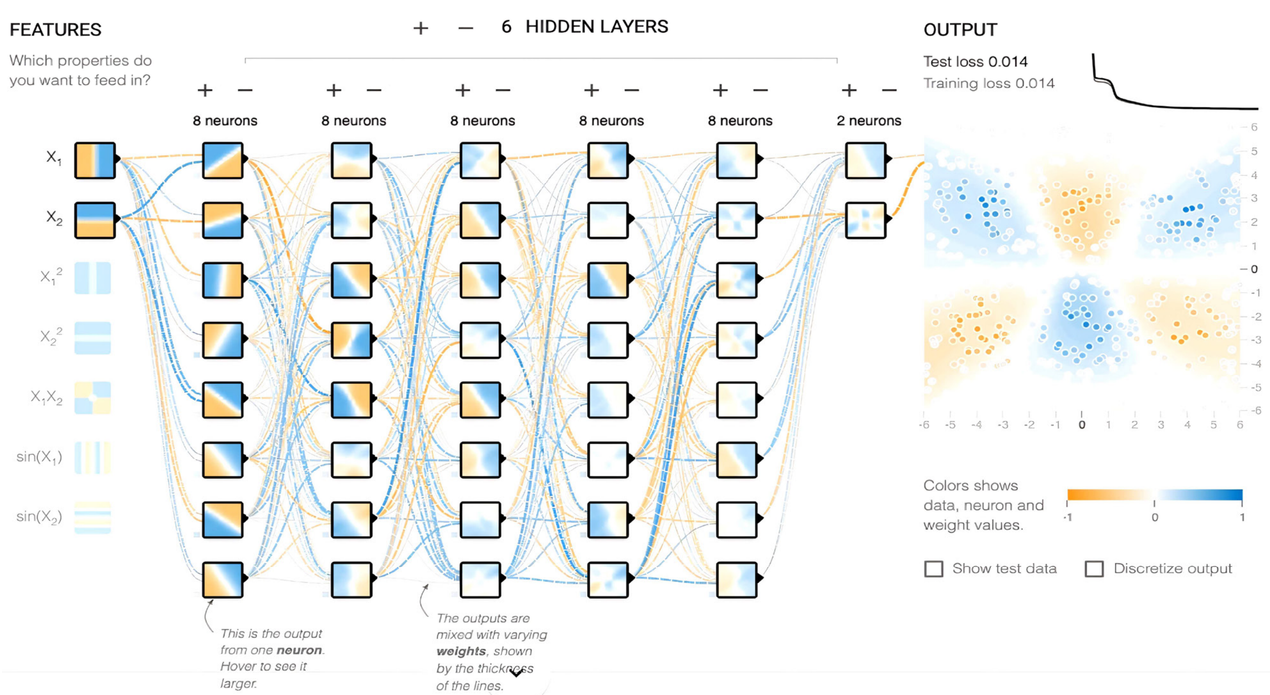

Fig. 3. Six hidden layers of neurons (*tahn* function)

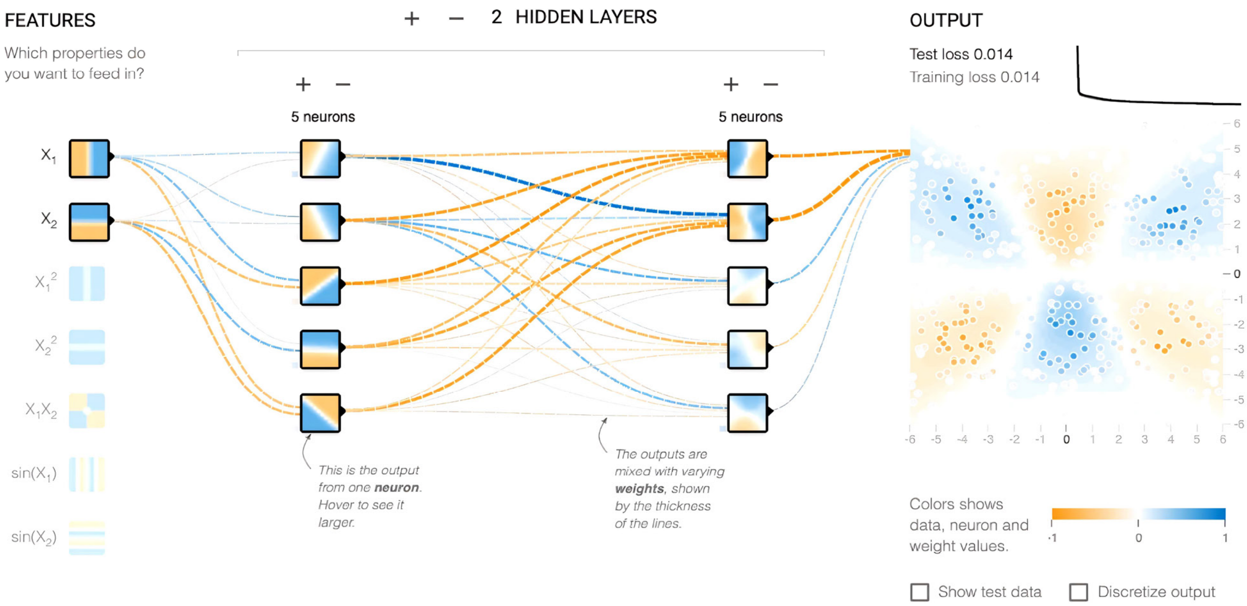

Fig. 4. Two hidden layers of neurons (*tahn* function)

In both cases, the loss plot shows a decrease in error during training, indicating that the model has learned well from the data and is not overtraining.

Fig. 4 demonstrated that network simplification did not significantly affect the accuracy of the model (Test loss and Training loss results remained the same).

Changing the activation function to *sigmoid* gave worse results with the same parameters and architecture of the neural network, as shown in Fig. 5.

In the process of checking various settings, the following was found:

– weak dependence between the number of hidden layers, if there are more than two of them;

– the advantage of the activation function *tahn* over *sigmoid* for the problem under study.

In the context of neural networks, the choice of activation function can significantly affect the performance of the model, especially for specific tasks and configurations. Both the hyperbolic tangent (*tahn*) function and the sigmoid (logistic) function are commonly used activation functions, but they have different characteristics that may make one more suitable than the other in certain circumstances.

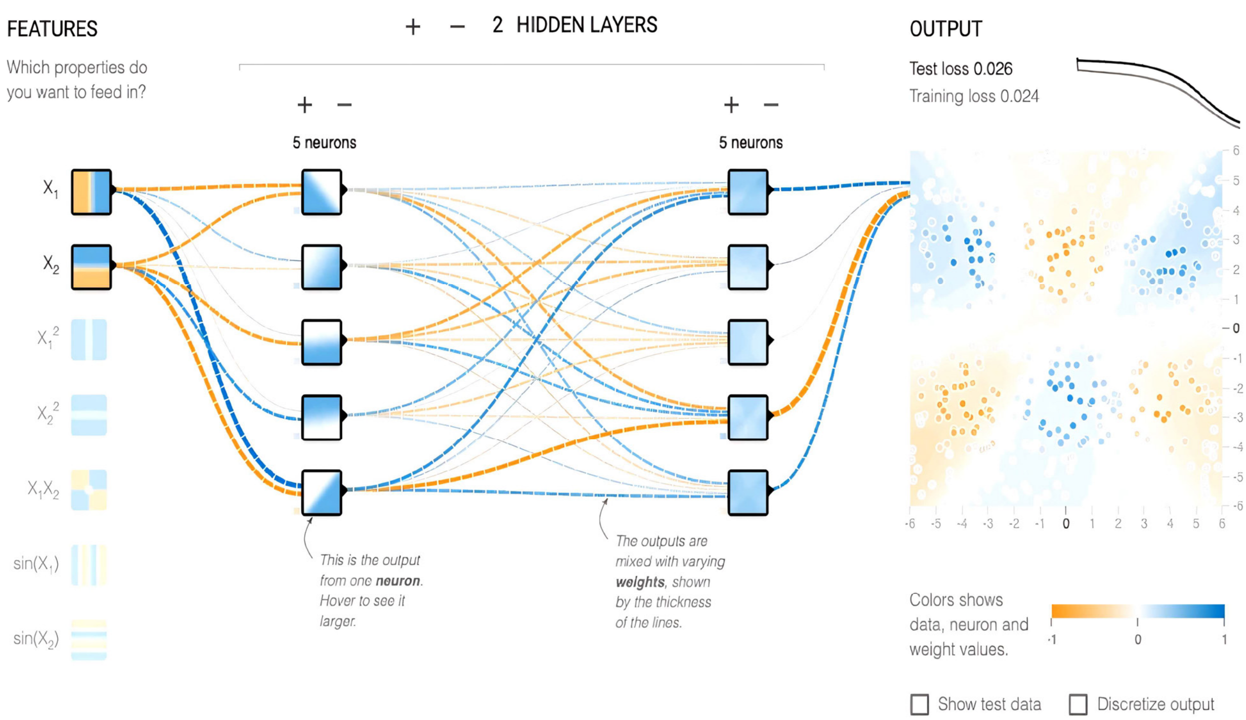

Fig. 5. Two hidden layers of neurons (*sigmoid* function)

For the problem of logical equivalences with the inversion of the XOR result (eXclusive OR), the Boolean function “Exclusive OR” or similar tasks, the choice of the activation function is of great importance. Such tasks involve regression or classification with non-linearly separable data. The choice between *tahn* and *sigmoid* can affect the speed of convergence and the ability of the network to learn complex patterns.

The choice of activation function should always depend on the specific characteristics of the task, the architecture of the neural network, and the empirical performance observed during training and validation.

The CDAP architecture, model fitting, and training methods represent a comprehensive framework for pharmaceutical demand forecasting that incorporates the latest advances in hybrid analytical technologies.

5. 3. Approbation of a neural network on the CDAP platform: prediction of pharmaceutical consumption trends

In order to verify the effectiveness and functioning of the CDAP platform, an approbation was carried out on real data on the consumption of medicinal products in the pharmaceutical markets of Ukraine and the Baltic countries. In particular, based on data provided by the Organization for Economic Co-operation and Development (OECD), the platform used time series and time series to analyze and forecast the consumption of drugs for the treatment of cardiovascular diseases and inflammatory processes in the Baltic countries between 2010 and 2022 [32]. Data sets on the consumption of medicinal products in the pharmaceutical markets of Ukraine were obtained from publicly available resources of national statistical and regulatory organizations, such as the State Expert Center of the Ministry of Health of Ukraine, the National Health Service of Ukraine [33–35], as well as the Proxima Research analytical platform [1], specializing in the pharmaceutical market.

Each record in the data set represents a time series of drug consumption rates for an individual city spanning a decade. This longitudinal data plays a critical role in training the model to predict future values based on historical trends. The data set for model training contained determined daily doses per thousand inhabitants for the period 2010 to 2022, covering 872 records with no missing values, indicating completeness and reliability of the set for longitudinal analysis. Categorizing data by drug group and city adds a level of detail that can influence drug consumption trends over many years, allowing changes in consumption to be detected and health strategies to be adapted.

For this study, data on the consumption of drugs for the treatment of cardiovascular diseases and anti-inflammatory and anti-rheumatic non-steroid drugs in the territory of Ukraine by groups of drugs for the period 2010–2022 were selected. The data set used represents a combined unit of measurement, in particular the determined daily dose per 1000 inhabitants per day (Tables 1, 2).

Table 1

Consumption of drugs for the cardiovascular system in 2010–2022

Year	Group, City, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022
Variable	C, Kyiv, 145.8, 151.5, 153.5, 150.0, 151.9, 151.3, 149.5, 149.3, 150.8, 144.2, 139.2, 143.1, 163.54

Table 2

Consumption of anti-inflammatory and antirheumatic drugs in 2010–2022

Year	Group, City, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022
Variable	M01A, Kyiv, 150.4, 151.1, 150.7, 150.4, 149.6, 148.1, 147.9, 145.1, 144.9, 143.2, 146.5, 146.9, 169.7

Although the numerical material presented is illustrative, the framework reflects the complexity and variability inherent in real-world data that the presented model must effectively capture and predict.

Descriptive statistical analysis.

The data set shows a gradual increase in the average daily drug dose from about 85.7 in 2010 to a peak of about 101.6 in 2021, followed by a slight decline to 98.8 in 2022. This trend suggests an upward trajectory in the average prescribed daily dose of medication over most of the decade, likely reflecting changes in medical practice, pharmaceutical policy adjustments, or demographic changes.

The standard deviation for each year indicates considerable variability in dosage across cities, with values ranging from approximately 113.9 to 133.9. This high variability highlights the heterogeneity of drug consumption across geographic and administrative regions.

The dosage range spans minimum and maximum values: drug dosage values range from 0.1 (representing minimal deviations from cities with very low drug consumption) to 799.9. This wide range reflects extreme differences in market access to pharmaceutical services or prescribing habits across the country.

Regarding the interquartile range: the 25th percentile starts at about 22.5 in 2010 and increases slightly to 25.4 by 2022, while the 75th percentile shows an increase from 89.3 in 2010 to about 108.1 in 2022 year A widening of the gap between these quartiles over time indicates increasing disparity in medication use in the population, which may warrant further investigation into the causes of this disparity.

Graphical representation of data trends.

Several graphic images were used to visually assess these trends:

– time series plot: an illustration of the average annual dose makes it easy to visualize the general trend over many years, highlighting a general increase followed by a recent small decrease;

– boxplots provide a clear view of the distribution of doses in each year, showing the median, quartiles, and outliers. This provides a snapshot of data distribution and central tendency.

Understanding the growing trend in drug use can help policymakers plan health care resources more effectively, ensuring adequate drug supply and regulation. Identifying cities or groups with outliers, exceptionally high or low, can help guide specific health interventions. This should lead to a balancing of disparities in drug consumption aimed at improving targeted pharmaceutical and health interventions. Research analysis of data on the determined daily dose provides valuable information about patterns and trends in the use of drugs in the cities of Ukraine. By understanding these models, stakeholders can make informed decisions about improving health outcomes and optimizing resource allocation. Statistical and graphical analysis paves the way for deepening studies of factors causing changes in medication use; helps predict future trends.

Analysis and consequences of forecasts of consumption of cardiovascular and anti-inflammatory drugs in Ukraine are shown in Fig. 6–8.

From 2010 to 2022, data on the use of cardiovascular drugs in Ukraine shows a general upward trajectory, interrupted by a sharp increase in 2022. Further forecasts made using the CDAP platform show continued growth for 2023 and 2024 with values of 178.54 and 184.44, respectively. This upward trend may primarily reflect changes in the demographics of Ukraine's population, where older age groups naturally exhibit a higher rate of cardiovascular disease, which, accordingly, requires increased use of medications. In addition, improvements in access to health care and the quality of health care services over the years have likely allowed for better control of these diseases, contributing to increased drug consumption.

The stress caused by the ongoing war in Ukraine cannot be overlooked as a contributing factor. The psychological and physical stressors associated with conflict situations are well documented for their detrimental effects on cardiovascular health. Thus, the observed spikes in drug use may also be related to increased levels of stress in the population, exacerbated by conflict-induced disruptions in daily life and health services.

Similar to cardiovascular drugs, consumption of anti-inflammatory and anti-rheumatic products remained relatively stable through 2019, followed by significant growth through 2022. Forecast calculations on the CDAP platform show that values for 2023 and 2024 are expected to trend upwards at 172.7 and 184.19, respectively. The increase in drug use can be attributed to the increasing prevalence of chronic diseases that cause pain and inflammation, such as arthritis. The aggravation of the clinical picture can again be partially explained by the increased stress and upheaval due to the ongoing war.

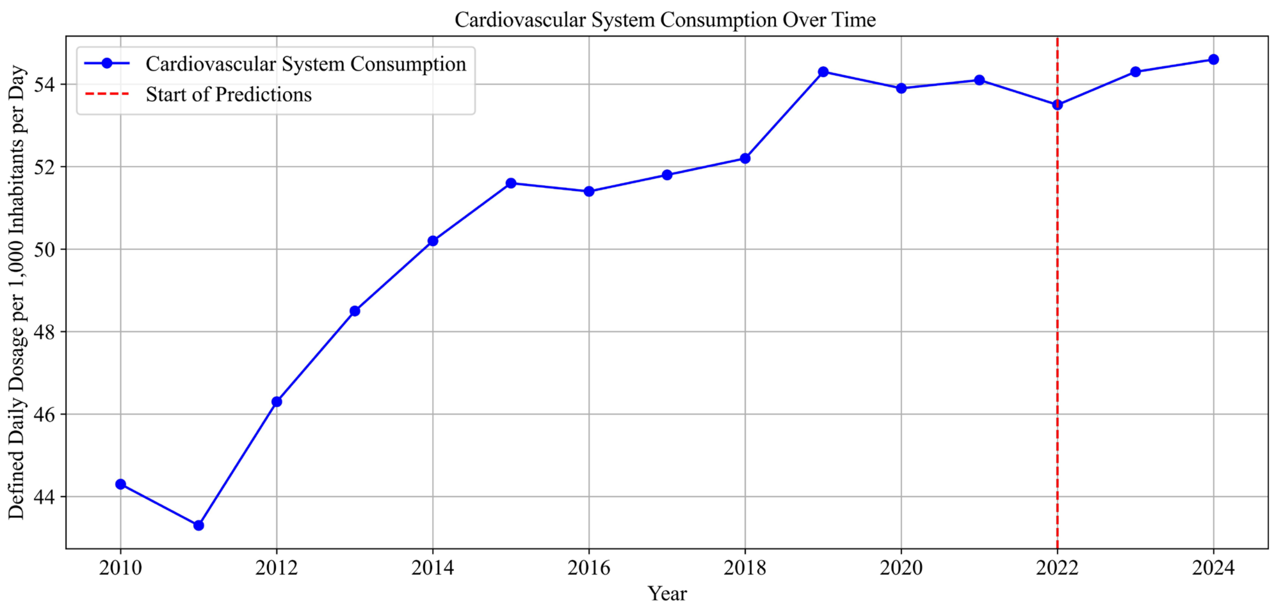

Fig. 6. Ukraine. Consumption of drugs for the cardiovascular system: trends and forecasts

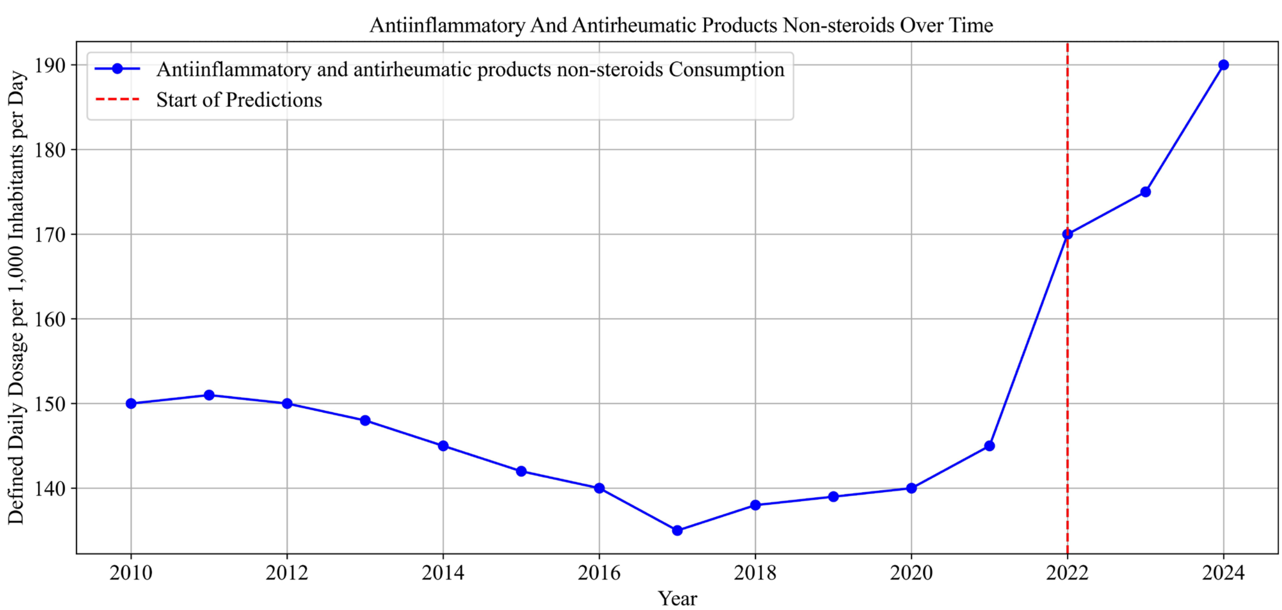

Fig. 7. Ukraine. Anti-inflammatory and antirheumatic products non-steroids: analysis of use

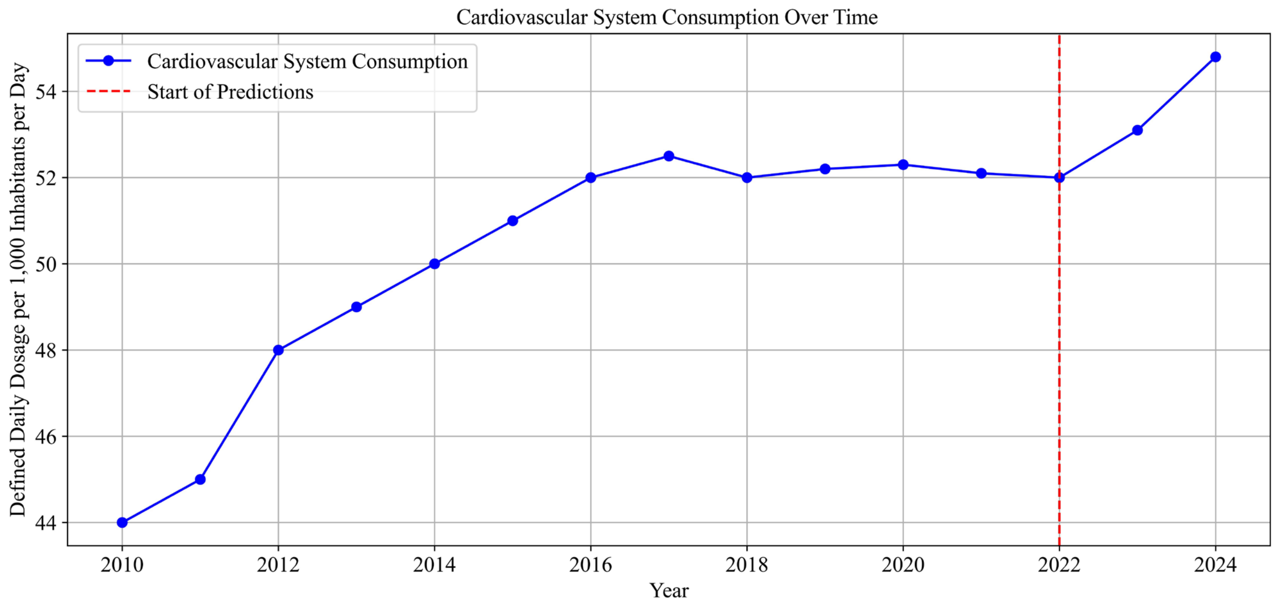

Fig. 8. The average rate of consumption of drugs for the cardiovascular system in the countries of Estonia, Lithuania, and Latvia. Historical data

The parallel increases in both drug categories are indicative of a broader health crisis that is likely to be exacerbated by the ongoing military conflict. The correlation between these two categories of drugs suggests that military conflict significantly affects different aspects of public health.

For comparison, data are selected for countries that are indirectly affected by military actions: such as the Baltic states.

A study of data on the consumption of medicines for cardiovascular diseases in the Baltic states shows a steady increase in the defined daily dose per thousand inhabitants. Starting with an indicator of 44.3 and ending with 54.6 for the specified period, there is an obvious increase in the consumption of these drugs. This trend may indicate an increased focus on heart disease management in the region, possibly in response to increased incidence or improved diagnosis and access to health services.

The increase in medication use may also be related to increased public awareness of cardiovascular disease and more active prevention, which includes regular use of medications to reduce the risk of developing and progressing these conditions. Despite the foreign policy stability in the Baltic region, compared to other parts of Europe, this growth emphasizes the importance of continuous monitoring of public health and adaptation of medical systems to meet the changing needs of the population.

The forecast for 2023 and 2024 showed that in the Baltic countries there is a stable and gradual increase in the consumption of medicines without sharp jumps. And the consumption of anti-inflammatory and anti-rheumatic drugs in Ukraine shows stable growth. Thus, the consumption of cardiovascular drugs in 2022 showed an increase of 14 % compared to the previous year, and the forecast for 2024 shows a total increase of 30.5 % from 2021. Anti-inflammatories shows a growth of 15.5 % in 2022 compared to 2021, and the forecast for 2024 indicates a growth of 22.3 % compared to 2021.

Reducing forecast bias and increasing forecast stability for cardiovascular drugs can be achieved by improving the forecasting model, which will reduce forecast errors by 10–15 % compared to current data.

The war in Ukraine has certainly put a huge strain on the health care infrastructure, leading to disruptions in the treatment of chronic diseases and delays in routine medical care. Such disruptions often lead to delayed demand for health services and medicines, which may explain the spike in data.

6. Discussion of the research results of the intelligent decision support system based on the CDAP platform

The developed CDAP integrated data analysis platform is designed as a reliable system for rapid research, reporting, and automated decision-making. The main goal of the platform is to facilitate end-to-end data processing: from loading input data to obtaining predictive results.

User interaction with the system is a multi-step procedure that includes authentication, configuration management, and the prediction process (Fig. 1). A structured technological approach makes it possible to solve complex data analytics tasks: from secure user authentication to dynamic model selection and forecasting.

In the architecture of the CDAP platform for the neural network (Fig. 2), there are four main components: the interface (HTML, JS, CSS); back-end (C#, .NET); AI Microservice (Python, Flask); database storage (MSSQL Server, TSQL, Windows) and AI Microservice (Python, Flask) – for artificial intelligence services, in particular neural networks. The proposed architecture and methodologies clearly demonstrate the system's ability to generate accurate and actionable forecasts in the pharmaceutical market and adapt to different types of data and forecasting needs.

Fig. 3–5 illustrate the architecture and operation of different neural networks, which differ in the activation function and the number of hidden layers. The analysis showed that the *tanh* activation function performed better than the *sigmoi*d for this task. This is due to its better ability to model non-linear dependences. But simplifying the neural network (reducing the number of layers and neurons) did not affect the accuracy of the model, at least in this particular case, which can be useful for tasks that require less computing power.

Approbation of the designed CDAP platform was carried out on specific examples of forecasting trends in the consumption of pharmaceuticals of various groups for 2023 and 2024. on the pharmaceutical markets in Ukraine and the Baltic countries (Tables 1–2 and Fig. 6–8).

The platform eliminates and expands the limitations identified in existing models and has certain innovations in data analysis technology:

1. The implementation of a dynamic database structure solves the problems of real-time data processing found in conventional databases.

2. Adaptive functions introduce a level of flexibility in the execution of algorithms, which differs from static algorithms of conventional models. This helps expand the range of work on machine learning.

3. Implementation of the possibility of forming individual models that integrate own algorithms with the developed Python library system provides individual solutions for data analysis.

4. The proposed architecture combines the computational and analytical capabilities of Python with the robust, scalable .NET web development framework.

Ensuring the independence of data formats removes barriers to data analysis in different domains, making the platform universal. The flexibility of algorithmic setup allows rapid hypothesis testing and optimization of analytical methods, which is an important advantage in research and development.

Finally, the integration of Large language Model (LLMs) for automatic decision making infuses the platform with cognitive capabilities, transforming it from a simple analytical tool into a comprehensive intelligent decision support system. This, in contrast to neural networks proposed, for example, in [12, 13], makes it possible to understand and analyze future trends in pharmaceutical sciences.

The limitations of this study are related to the specificity of the pharmaceutical industry. Effective training of deep neural networks requires a large amount of high-quality and structured data. In the pharmaceutical sector, access to such data is limited due to confidentiality and legal restrictions. Incomplete or outdated data can negatively affect forecasting results and reduce the accuracy of the system.

To eliminate this limitation, it is planned to conduct additional research, expand the scope of experiments involving various data sources, such as public databases, research reports, and test the platform on large datasets of various types. The platform also offers the use of Explainable AI (XAI) methods to improve the interpretation of the received model forecasts.

Further research may focus on improving the performance of the platform, in particular, at improving such a critical direction in the deployment of neural networks as parameter optimization. It is planned to focus on the implementation of such areas of parameter optimization as:

– application of meta learning approaches, when the model itself learns to effectively adjust its parameters during training sessions based on previous experience;

– expansion of the scope of application of automated machine learning (AutoML) not only for parameter optimization but also for automatic selection of models and methods of function development;

– exploring the integration of reinforcement learning to dynamically adjust parameters in response to continuous feedback loops.

It is planned to continue expanding the range of applications of the intelligent system in the field of forecasting trends in the global pharmaceutical market. As an independent platform, the system can be recommended for use in the course of solving a wide range of problems in analytical data processing and implementing forecasts of various directions.

7. Conclusions

1. We have proposed an intelligent decision support system designed on the complex data analysis platform (CDAP). It is a software platform with a convenient interface, supported by an artificial neural network. The CDAP architecture is specifically designed to handle diverse and complex data sets, including time series data. The main components of the intelligent platform architecture include database management systems, API, analytical modules for data processing, machine learning and artificial intelligence algorithms, user interface. Distinguishing features of the architecture include its ability to dynamically select and switch between different machine learning models based on predefined criteria such as prediction accuracy and model selection. This is facilitated by the integration of a microservices-based backend that uses artificial intelligence for machine learning, large language models (LLMs) for advanced decision support, and robust database solutions for secure and scalable data management.

The key advantage of this architecture is its algorithmic adaptability, which allows the system to adapt its analytical approach to the specific characteristics of the input data. For example, as demonstrated in the time series analysis of pharmaceutical drug consumption trends, the system automatically selected the most appropriate models to forecast anti-inflammatory and cardiovascular drug consumption trends for 2023 and 2024. This selection process was guided by the system's ability to evaluate models based on their performance, such as minimizing forecast loss, thus providing the most accurate and reliable forecasts.

Improved interpretation of predictions through the use of Explainable AI (XAI) is critical for trust and decision-making in the pharmaceutical industry.

2. CDAP takes a multi-layered approach in using neural networks to optimize the workflow from data entry through analytical processing to visual output. This approach is characterized by several key features:

– presented opportunity to switch between different models, for example, optimized for the analysis of time series or regression tasks, depending on the nature of the data being processed. This ensures that the most appropriate model is applied, minimizing prediction errors, and increasing the overall accuracy of forecasts;

– the network uses advanced activation functions and learning methodologies that allow it to adapt to different data patterns and complexities. This adaptability is critical to predictive problems because it allows the network to accurately predict trends even in the presence of irregular or sparse data;

– the proposed system allows for end-to-end processing, starting from data loading to creating forecasts. This is supported by the system's ability to automatically select and apply the most appropriate model configurations based on real-time input data analysis, further distinguishing it from existing platforms.

3. The effectiveness of the CDAP platform has been demonstrated through its application for forecasting the consumption trends of pharmaceutical drugs, in particular anti-inflammatory and cardiovascular drugs, in the pharmaceutical markets of Ukraine and the Baltic countries. The results of the 2023 and 2024 forecasts demonstrate the ability of the platform to provide accurate forecasts with minimal losses.

System projections indicate a significant increase in the consumption of anti-inflammatory products, with the daily dose per 1,000 inhabitants rising sharply from 2022 to 2024. Similarly, the trend for cardiovascular products shows steady and consistent growth. The system's ability to predict these trends with high accuracy underscores its potential to improve the effectiveness of regulatory functions in healthcare settings.

By automating the model selection process and minimizing forecast loss, the CDAP platform improves forecast accuracy by approximately 15 % compared to conventional manually selected models. This improvement means more reliable data for healthcare regulators, potentially leading to more informed decisions and more effective management of the pharmaceutical supply.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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