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# NORMALIZED INPUT VECTORS: THE PRIMARY STAGE OF DATA PREPARATION

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**Abstract.** The protection of agricultural crops from pests in Northern Kazakhstan, such as the striped bread flea (Phyllotreta vittula) occupies an important place in crop production, allowing not only to preserve the harvest, but also to strengthen food security. Early detection of the pest to find solutions remains a challenge in the field of sustainable agriculture. The most promising way to protect plants from pests is the use of new technologies, such as machine learning, neural network. We investigate the factors for the identification of the striped bread flea, in order to obtain versatile information: the collection and processing of data characterizing the species composition, distribution and development of the pest is organized, we collect data for the last ten years in Northern Kazakhstan. Machine learning methods will use numerical data to identify the pest of plants. The use of machine learning in agriculture makes it possible to increase the efficiency and accuracy of farming with less labor and high quality products. The next stage of the research is to normalize all the collected data using data normalization in the Python program and further use them in neural network training. The normalization process enters the initial stage, after data collection during forecasting in machine learning.

**Keywords:** data normalization, machine learning, forecasting, agriculture, bread striped flea

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# НОРМАЛАНҒАН КІРІС ВЕКТОРЛАРЫ: ДЕРЕКТЕРДІ ДАЙЫНДАУДЫҢ БАСТАПҚЫ КЕЗЕҢІ

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**Аңдатпа.** Солтүстік Қазақстандағы ауыл шаруашылығы дақылдарыннан жолақты бүрге (Phyllotreta vittula) сияқты зиянкестерден қорғау өсімдік шаруашылығында маңызды орын алады, бұл егінді сақтап қана қоймай, азық-түлік қауіпсіздігін нығайтуға мүмкіндік береді. Зиянкестерді ерте анықтау ауыл шаруашылығы саласында шешімдерді табу үшін әлі де проблема болып табылады. Өсімдіктерді зиянкестерден қорғаудың ең перспективалы жолы машиналық оқыту, нейрондық желі сияқты жаңа технологияларды пайдалану. Нанның жолақты бүргесін анықтау факторларын зерттейміз, жан-жақты ақпарат алу үшін: зиянкестердің түрлік құрамын, таралуы мен дамуын сипаттайтын деректерді жинау және өңдеу ұйымдастырылады, Солтүстік Қазақстанда соңғы он жылдағы деректерді жинаймыз. Машиналық оқыту әдістері өсімдік зиянкестерін анықтауға арналған сандық деректерді пайдаланады. Ауыл шаруашылығында машиналық оқытуды қолдану еңбек шығындарын азайтып және өнім сапасын арттыруға мүмкіндік береді. Зерттеудің келесі кезеңі-Python бағдарламасындағы деректерді қалыпқа келтіруді қолдана отырып, барлық жиналған деректерді қалыпқа келтіру және оны нейрондық желіні оқытуда одан әрі қолдану. Қалыпқа келтіру процесі машиналық оқытуда болжау кезінде деректерді жинағаннан кейін бастапқы кезеңге енеді.

**Түйін сөздер:** деректерді қалыпқа келтіру, машиналық оқыту, болжау, ауыл шаруашылығы, жолақты нан бүргесі

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# НОРМАЛИЗОВАННЫЕ ВХОДНЫЕ ВЕКТОРЫ: ПЕРВИЧНЫЙ ЭТАП ПОДГОТОВКИ ДАННЫХ

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**Аннотация.** Защита сельскохозяйственных культур от вредителей в Северном Казахстане, таких как хлебная полосатая блошка (Phyllotreta vittula) занимает важнейшее место в растениеводстве, позволяя не только сохранить урожай, но и укрепить продовольственную безопасность. Раннее выявление вредителя для поиска решений по-прежнему остается проблемой в области устойчивого сельского хозяйства. Наиболее перспективным способом защиты растений от вредителя является использование новых технологий, таких как машинное обучение, нейронная сеть. Исследуем факторы по выявлению хлебной полосатой блошки, с целью получения разносторонней информации: организуется сбор и обработка данных, характеризующих видовой состав, распространение и развитие вредителя, собираем данные за последние десять лет в Северном Казахстане. Методы машинного обучения будут использовать числовые данные по идентификации вредителя растений. Применение машинного обучения в сельском хозяйстве позволяет повысить эффективность и точность ведения сельского хозяйства с меньшими затратами труда и высоким качеством продукции. Следующим этапом исследования является нормализовать все собранные данные, используя нормализацию данных в программе Python и в дальнейшем применение их в обучении нейронной сети. Процесс нормализации входит в начальный этап, после сбора данных при прогнозировании в машинном обучении.

**Ключевые слова:** нормализация данных, машинное обучение, прогнозирование, сельское хозяйство, хлебная полосатая блошка

**Финансирование:** Исследование проводилось из личных средств авторов.

**Конфликт интересов:** Авторы заявляют об отсутствии конфликта интересов.

**Introduction**

Agricultural productivity makes a significant contribution to the economy of Kazakhstan. Pests of grain crops seriously affect the main production and cause great damage to the economy. One of such permanent pests of grain crops is the bread striped flea.

Health monitoring and early diagnosis of pests of grain crops is the most important task of sustainable agriculture. Information about the early diagnosis of certain plant diseases can facilitate pest control by choosing the right methods of combating them to increase grain yield. Manual identification of disturbances in grain crops can lead to inaccurate measurements of pesticides.

This work is carried out manually by agronomists, the above problem requires the intervention of the latest technologies for predicting the appearance of plant pests. Therefore, a method for recognizing pests of agricultural crops based on a modified capsule network has been proposed in world science (Zhang, 2022). The modified capsule network is used to improve the traditional convolutional neural network, and the attention module is introduced to capture the most important classification features and accelerate network learning. The results of experiments with a set of images of pests confirm that the proposed method is effective and feasible in classifying various insect species in field crops and can be applied in the agricultural sector for plant protection.

Currently, machine learning is very widely used in agronomic research. The use of machine learning in agricultural data processing makes it possible to increase the efficiency and accuracy of farming with less labor and high product quality. Machine learning has emerged together with big data technologies and high-performance computing to create new opportunities for analyzing, quantifying and understanding processes that require large amounts of data in agricultural operating environments.

A comprehensive review of the research of foreign scientists on the application of machine learning in agricultural production systems is presented. The filtering and classification of the submitted articles demonstrate how agriculture will benefit from machine learning technologies. By applying machine learning to sensor data, farm management systems are transformed into real-time AI-enabled programs that provide detailed recommendations and analytical information to support farmers' decision-making and actions (Liakos, 2018).

Modern technologies, such as the Internet of Things (IoT), lay the foundation for precision farming, which minimizes human labor and costs, as well as increases agricultural productivity. The Internet of Things generates large amounts of data that can be used for practices such as crop monitoring or disease detection. The analysis and interpretation of these data make it possible to understand the relationships between various agricultural factors, such as soil characteristics and climatic variables. This contributes to timely and informed decision-making and planning. Machine learning plays a central role in these decision support systems by modeling complex patterns that may exist in the data (Condran, 2022).

The data generated in modern agricultural operations is provided by a variety of different sensors that allow a better understanding of the working environment (interaction of dynamic crops, soil, and weather conditions) and the operation itself (equipment data), which leads to more accurate and faster decision-making.

Tasks are usually divided into various broad categories depending on the type of training (supervised/unsupervised), learning models (classification, regression, clustering and dimensionality reduction) or learning models used to implement the selected task.

In general, the effectiveness of a machine learning solution depends on the nature and characteristics of the data and the performance of the learning algorithms. In the field of machine learning algorithms, classification analysis, regression, data clustering, foreign economic activity - for the effective construction of data-driven systems, there are methods of structure design and dimensionality reduction, the study of associative rules or reinforcement learning (Sarker, 2021).

Machine learning, including neural networks, prompted the processing and analysis of big data obtained in the research of the agricultural sector. To carry out machine learning, you need to perform a number of actions that include: preparation of reliable data, normalization of data suitable for machine learning algorithms, data transformation, method selection (neural network architecture), re-sampling, building a neural network model and training a neural network. The main and initial stage in data training is the normalization of the data itself.

Data normalization is a fundamental preprocessing step for data mining and data-based learning. However, finding a suitable method for normalizing time series is not an easy task. This is due to the fact that most traditional normalization methods make assumptions that are not valid for most time series. The first assumption is that all time series are stationary, i.e. their statistical properties, such as mean and standard deviation, do not change over time. The second assumption is that the time series is considered uniform. None of the methods currently available in the literature solves these problems. Therefore, a new method of normalization of time series is proposed in world science. The method, called Adaptive Normalization, was tested together with an artificial neural network in three prediction tasks. The results were compared with the other four traditional normalization methods and showed an increase in accuracy in both short- and long-term forecasts (Ogasawara, 2010).

The use of satellite images for monitoring drought in agriculture, both regionally and globally, is attracting increasing attention of researchers. Since agricultural drought is one of the most destructive agricultural threats worldwide, which can lead to significant losses in agriculture and water shortages. Foreign scientists first analyzed the correlation between the temperature of the earth's surface and the normalized difference vegetation index using time series under different vegetation growth conditions, the data obtained showed that the index of the temperature regime of vegetation can be used only in the warm season (late spring and summer periods), when negative correlations are observed between the temperature of the earth's surface and the normalized difference vegetation index (Hu, 2019).

Thanks to the capabilities of nonlinear modeling, prediction networks with deep learning have become widely used for intelligent agriculture. Since sensor data contains noise and complex nonlinearity, and it was necessary to increase their performance, scientists proposed a reversible network for automatic normalization of selection. Integrating the level of normalization and renormalization for evaluation and selection of the normalization module of the forecasting model. Prediction accuracy has been effectively improved by scaling and transforming input data using trainable parameters. The results of the forecasting application showed that the model has a good forecasting ability and adaptability for greenhouses in the system of intelligent agriculture (Shi, 2022).

Plant diseases are one of the problems that can lead to losses in the production and economy of the agricultural sector. Early detection of this disease to find solutions and treatments remains a challenge in the field of sustainable agriculture. Currently, image processing methods and machine learning methods are used to successfully detect plant diseases. In order to increase efficiency in the multiclass classification of plant diseases, automatic diagnostics of leaf diseases is proposed. This is the development of a system for a convolutional neural network with a deep learning approach based on batch normalization for the classification of plant diseases. The importance of using deep learning technology is to make the system end-to-end, automatic, accurate, less expensive, and more convenient to detect plant diseases by their leaves (Fahad, 2021).

In the research conducted by, a total of 50 indicators from the categories of productivity, stability, efficiency, durability, compatibility and equity in agriculture are used to find out which normalization method is most suitable for further mathematical analysis to develop a final composite indicator. In order to understand the consistency and quality of normalization measurement methods and compare the advantages and disadvantages of various selected normalization processes, indicators of agricultural sustainability were considered (Talukder, 2017). Each of the different normalization methods had its advantages and disadvantages. This research showed that the rules of proportional normalization and hybrid aggregation of the arithmetic mean and geometric mean are suitable for the selected data set and that this method has wider application for the development of composite indicators for assessing the sustainability of agriculture.

In machine learning tasks, the source data is often set in different units of measurement and types of scales. Such data should be transformed into a single representation by normalizing or standardizing them. The paper shows the difference between these operations. The main types of scales, operations on the data presented in these scales, and the main options for normalization of functions are systematized. The rules for separating the features of tree classifiers are invariant to the scales of quantitative features. They only use the comparison operation.

Perhaps due to this property, the classifier of the "random forest" type as a result of numerous experiments is recognized as one of the best when analyzing data of different nature (Starovoitov, 2021).

Thus, it can be seen from the studied scientific works of world scientists that the following methods have been studied and proposed: the influence of adaptive normalization on the prediction of time series using artificial neural networks; the use of satellite images to monitor drought in agriculture; reversible automatic normalization network for greenhouses in the intelligent agriculture system; development of a system based on batch normalization for the classification of plant diseases; rules of proportional normalization and hybrid aggregation for assessing the sustainability of agriculture; a classifier of the "random forest" type transformed into a single representation by normalizing them. But the studied scientific sources do not provide complete information about the factors and normalization of input data on agricultural pests, including the striped bread flea, for training in a neural network. Analysis of literature sources has shown that the normalization of data regarding the processing of data on pests in the agricultural sector, such as the bread-striped flea, remains poorly studied. This area requires a more thorough analysis, taking into account statistical data on factors affecting the growth of agricultural pests, in particular the bread striped flea, and obtaining normalized data for further training in the neural network.

The purpose of this research is to determine the factors and indicators for the normalization of input data used in predicting the growth dynamics of the main pest based on an analytical system to improve yields. To achieve the goal, the following tasks were set: a) determination of factors for the identification of plant pests (numerical data of which will be data for machine learning) and data collection b) normalization of the collected data for further use in neural network training. The normalization process enters the initial stage, after data collection during forecasting in machine learning and affects the learning outcome. Therefore, it is important to consider this stage more carefully.

**Methods and materials**

Data normalization is an important step in data preparation before training the neural network. The result of training depends on correctly normalized data. And also, before data normalization, by analyzing previously researched data on pest population growth, factors were selected that reflect the dependence of pest population growth.

There are many ways to normalize and scale feature values to a common range for use in various machine learning models. They can be divided into two large groups: linear and nonlinear, depending on the function used. Nonlinear normalization uses logistic sigmoids or hyperbolic tangent functions with calculated ratios. With linear normalization, changes in variables are carried out proportionally according to a linear law.

The need to normalize data sampling is the very nature of the variables used in neural network models. Because they differ in a physical sense, their absolute values are often very different from each other. For example, a sample may contain concentrations measured in tenths or hundredths of a percent, as well as a pressure of hundreds of thousands of pascals. Data normalization allows you to move all numeric values of the variables used to the same change area.

To perform data normalization, it is necessary to know exactly the limits of change (theoretically possible minimum and maximum values) of the values of the corresponding variables. Then they will correspond to the boundaries of the normalization interval. If the limits of variable variation cannot be set precisely, they are set taking into account the minimum and maximum available data samples.

Forecasting methods in machine learning, including: review and analysis of the state of the number of pests of grain crops in Kazakhstan; analysis of existing and promising methods of accounting and forecasting the current state of crops. The general methodology of the research was the application of a systematic approach. The following methods were used to solve the problems: analysis, scientific generalization, comparison, experimental research. During the analysis, a comprehensive analysis of the state of forecasting the yield of grain crops for the nth number of years. With the help of scientific generalization, the results of existing experiments in the field of research will be reviewed and summarized.

To obtain normalized data, first of all, factors for identifying plant pests were determined (numerical indicators of pest characteristics, the data of which will be data for machine learning) and data collection: exit from wintering sites on grasses, abundance, migration to crops, damage to the leaf surface, mating, hatching of larvae, the emergence of a new generation, going to wintering grounds.

The bread striped flea is a permanent pest of grain crops. Under the condition of a warm and humid spring, and also taking into account the accumulated stock of the population due to successful overwintering, a widespread increase in the pest population is expected. Its harmfulness is largely manifested in dry, hot weather in the initial period of growth and development. At this time, the first leaf suffers most from the bread flea. Young plants are noticeably depressed, turn yellow and dry up. Early crops are damaged more than later ones. Another factor contributing to the development of the pest is the severe damage of plants by root rot. To a greater extent, barley and spring wheat are damaged, to a lesser extent – oats, corn. The harm caused by the phytophagus can be reduced by using insecticidal mordants, observing agricultural cultivation techniques, and, if necessary (due to their peculiarities of populating fields) – carrying out local edge treatments (band width – 50-100 m) with insecticides.

For the future, the forecast of the number of growth of the bread striped flea is associated with the phenophase of culture development suitable for the insect (1–2 leaves), as well as with the weather conditions of the year. The authors have revealed a direct dependence of the bread flea on temperature and the reverse on precipitation in the year of sowing (Kozulina, 2021).

Key aspects of the development include knowledge of system dynamics based on data from several seasons. An alternative approach was to construct models parameterized on the basis of independent controlled experiments aimed at identifying the response of organisms to a number of environmental factors. The two most popular examples are the phenological models of insect pests and infection models (Welch, 1978, Magarey, 2005). Such models can be used to determine how climate change may affect the frequency of pesticide use. In some cases, it is possible to assess the impact on the crop by converting pest intensity forecasts into crop loss forecasts.

The development and spread of the pest of agricultural crops are influenced by the weather and climatic conditions of the growing season. Accounting of all data was carried out on warm windless days in the ear phases from germination to tillering, and for normalization, data obtained only on windless days were taken. Thus, objective data were obtained, which are presented in Table 1 since 2011.

Table 1. Factors influencing the number of development of the bread striped flea (Northern Kazakhstan)

| North.Kaz. | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Exit from wintering grounds on grasses | 14 April-5 May | 10-21 April | 16-22 April | 21-25 April | 20-29 April | 11-19 April | 15-20 April | 20 April- 5 May | 10-25 April | 15 April-5 May | 17-23 April |
| Number (ex/m2) | 1-50 | 0,5-18 | 0,4-1,0 | 1-80 | 0,5-70 | 1-60 | 0,5-50 | 1,0-50 | 10 -38,3 | 1,0-40,0 | 1,0-50 |
| Migration to crops | I decade of June | May | 28-31 May | 24-28 May | 25-29 May to 2-4 June | 15-20 May | 25-28 May | 2-4 June | 24-26 May | 20 May | 29 May |
| Number (ex/m2) | 1,0-300 | 2,0-300 | 2,0-300 | 2,0-25 | 1,0-150 | 1,0-300 | 1,0-150 | 2,0-300 | 1,0-100 | 1,0-100 | 2,0-200 |
| Damage to the leaf surface (%) | 6-22 | 0,3-22,0 | 2-8 to 20-25 | 0,1-5,0 | 0,5-25,0 | 5-23 | 0,5-25,0 | 0,4-22,0 | 3-25,0 | 1,0-50,0 | 6-22 |
| Mating | 5-18 June | 26 May -6 June | 5-21 June | 9-16 June | 12-19 June | 5-20 June | 7-17 June | 28 May-7 June | 2-20 June | 28 May | 15-18 June |
| Hatching of larvae | from 28 June | 28 June -29 July | 25-26 June | late June | 18-22 July | 25 June | 27 June | 25 June | 20 June | 3-23 June | 15-28 June |
| The emergence of a new generation | 14-29 July | until mid-August | 17-24 July | 17-23 July | until mid-August | 20-25 July | 18-28 July | 18-25 July | until mid-August | 9-24 July | 15-25 July |
| number (ex/m2) | To 50 | to 47 | 1-35 | 2-35 | 2-40 | to 50 | to 40 | to 40 | to 40 | 5,0-51 | to 40 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Going to wintering grounds | 10 August-III decade September | 3-24 August | 17-20 August – 1st half of September | 18-21 August-III decade of September | 15-20 August | 18-22 August | 10-25 August | 18-25 August | 10-22 August | 14-25 August -7-10 September | 25 August -5 September |
| ..... | .... | .... | .... | .... | .... | .... | .... | .... | .... | .... | .... |

Thus, 10 factors were considered, the normalization results of which are shown in Table 1. To build a specialized normalization model, data from such factors as air temperature, relative humidity and leaf moisture, soil temperature, radiation, wind speed were included. This data is needed to reduce uncertainties during calibration and evaluation.

Other datasets at a lower level of detail may be collected from real fields to validate the model development and calibration performed using the detailed dataset.

Table 1 presents data in such units of measurement and ranges of values as in months, ex/m2, percentages, degrees. The measurement data was used in a numerical format, since the numerical format allows us to compare and normalize the data. And in such a way that none of them has any advantages over others. the main condition for proper normalization is that all signs should be equal in the possibilities of their influence.

After normalization, all numeric values of input features will be reduced to the same area of their change – some narrow range. Data normalization will allow us to prepare input data for machine learning and ensure the correct operation of computational algorithms (Peshawa, 2014).

Table 2. Lower pest data (initial stage) from Table 1

| Exit from wintering grounds on grasses | Number (ex/m2) | Migration to crops | Number (ex/m2) | Damage to the leaf surface (%) | Mating | Hatching of larvae | The emergence of a new generation | Number (ex/m2) | Going to wintering grounds |
|---|---|---|---|---|---|---|---|---|---|
| 14.04 | 20 | 01.06 | 100 | 6 | 05.06 | 28.06 | 14.07 | 20 | 10.08 |
| 10.04 | 9 | 10.05 | 100 | 1 | 26.05 | 28.06 | 10.08 | 15 | 03.08 |
| 16.04 | 0.4 | 28.05 | 100 | 8 | 05.06 | 25.06 | 17.07 | 7 | 17.08 |
| 21.04 | 30 | 24.05 | 2 | 1 | 09.06 | 30.06 | 17.07 | 7 | 18.08 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 20.04 | 15 | 25.05 | 50 | 5 | 12.06 | 18.07 | 10.08 | 8 | 15.08 |
| 11.04 | 20 | 15.05 | 90 | 5 | 05.06 | 25.06 | 20.07 | 10 | 18.08 |
| 15.04 | 20 | 25.05 | 45 | 2 | 07.06 | 27.06 | 18.07 | 8 | 10.08 |
| 20.04 | 18 | 02.06 | 35 | 3 | 28.05 | 25.06 | 18.07 | 8 | 18.08 |
| 10.04 | 10 | 24.05 | 10 | 3 | 02.06 | 20.06 | 10.08 | 8 | 10.08 |
| 15.04 | 15 | 20.05 | 10 | 7 | 28.05 | 03.06 | 09.07 | 11 | 14.08 |
| 17.04 | 17 | 29.05 | 33 | 6 | 15.06 | 15.06 | 15.07 | 9 | 25.08 |

Table 3. Upper data from Table 1

| Exit from wintering grounds on grasses | Number (ex/m2) | Migration to crops | Number (ex/m2) | Damage to the leaf surface (%) | Mating | Hatching of larvae | The emergence of a new generation | Number (ex/m2) | Going to wintering grounds |
|---|---|---|---|---|---|---|---|---|---|
| 05.05 | 50 | 10.06 | 300 | 22 | 18.06 | 30.06 | 29.07 | 50 | 20.09 |
| 21.04 | 18 | 20.05 | 300 | 22 | 06.06 | 29.07 | 15.08 | 47 | 24.08 |
| 22.04 | 1 | 31.05 | 300 | 20 | 21.06 | 26.06 | 24.07 | 35 | 15.09 |
| 25.04 | 80 | 28.05 | 25 | 5 | 16.06 | 30.06 | 23.07 | 35 | 20.09 |
| 29.04 | 70 | 02.06 | 150 | 25 | 19.06 | 22.07 | 15.08 | 40 | 20.08 |
| 19.04 | 60 | 20.05 | 300 | 23 | 20.06 | 25.06 | 25.07 | 50 | 22.08 |
| 20.04 | 50 | 28.05 | 150 | 25 | 17.06 | 27.06 | 28.07 | 40 | 25.08 |
| 05.05 | 50 | 04.06 | 300 | 22 | 07.06 | 25.06 | 25.07 | 40 | 25.08 |
| 25.04 | 38 | 26.05 | 100 | 25 | 20.06 | 20.06 | 15.08 | 40 | 22.08 |
| 05.05 | 40 | 20.05 | 100 | 50 | 28.05 | 23.06 | 24.07 | 51 | 10.09 |
| 23.04 | 50 | 29.05 | 200 | 22 | 18.06 | 28.06 | 25.07 | 40 | 05.09 |

Data normalization in Python is used to make the machine have to process a smaller range of data. The results depend on the choice of the correct normalization method. The popular *sklearn* method was chosen to normalize the data in this research. The work uses the *NumPy* and *sklearn* libraries for machine learning of the Python programming language. The *preprocessing* class is imported from the *sklearn* library. The *preprocessing* class allows access to the *normalize()* function. That is why this method is called the normalization method of the *sklearn* library. Next, a *NumPy* array is created with unique integer values, then the *normalize()* method from *preprocessing* is called and *numpy_array* is passed as a parameter. All integer data is normalized between zero and one.

**Results**

As a result of the research, more than 1000 input data were considered, taking into account the upper and lower bounds.

To begin with, we take the lower data in the form presented in Table 2 and normalize the data in the Python program, at the end we get the normalized data presented in Table 4.

Table 4. Normalized lower data from Table 2

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.127390 | 0.181468 | 0.009618 | 0.907339 | 0.054440 | 0.045911 | 0.254599 | 0.127663 | 0.181468 | 0.091460 |
| 1 | 0.091326 | 0.081866 | 0.091417 | 0.909622 | 0.009096 | 0.236957 | 0.255240 | 0.091690 | 0.136443 | 0.028016 |
| 2 | 0.144079 | 0.003593 | 0.251958 | 0.898245 | 0.071860 | 0.045451 | 0.225100 | 0.153330 | 0.062877 | 0.153420 |
| 3 | 0.351692 | 0.501462 | 0.402005 | 0.033431 | 0.016715 | 0.151441 | 0.502465 | 0.285332 | 0.117008 | 0.302214 |
| 4 | 0.294068 | 0.220111 | 0.367585 | 0.733702 | 0.073370 | 0.176969 | 0.265160 | 0.147914 | 0.117392 | 0.221285 |
| 5 | 0.108482 | 0.196526 | 0.147886 | 0.884366 | 0.049131 | 0.049721 | 0.246247 | 0.197214 | 0.098263 | 0.177659 |
| 6 | 0.222798 | 0.296274 | 0.371084 | 0.666617 | 0.029627 | 0.104585 | 0.400859 | 0.267684 | 0.118510 | 0.149322 |
| 7 | 0.313123 | 0.281248 | 0.032187 | 0.546871 | 0.046875 | 0.438278 | 0.391560 | 0.282342 | 0.124999 | 0.282498 |
| 8 | 0.254030 | 0.253018 | 0.608507 | 0.253018 | 0.075905 | 0.052122 | 0.507553 | 0.255042 | 0.202414 | 0.255042 |
| 9 | 0.320663 | 0.319810 | 0.427479 | 0.213206 | 0.149245 | 0.598044 | 0.065241 | 0.193378 | 0.234527 | 0.300195 |

Next, we take the upper data from Table 3, we also run it through the Python program and get the normalized data in Table 5.

Table 5. Normalized upper data from Table 3

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.016124 | 0.159647 | 0.032121 | 0.957879 | 0.070244 | 0.057664 | 0.095980 | 0.092819 | 0.159647 | 0.064146 |
| 1 | 0.068066 | 0.058231 | 0.064863 | 0.970519 | 0.071171 | 0.019604 | 0.094043 | 0.048785 | 0.152048 | 0.077900 |
| 2 | 0.071505 | 0.003244 | 0.100737 | 0.973300 | 0.064887 | 0.068326 | 0.084547 | 0.078091 | 0.113552 | 0.048957 |
| 3 | 0.230647 | 0.736892 | 0.258373 | 0.230279 | 0.046056 | 0.147931 | 0.276887 | 0.212501 | 0.322390 | 0.185052 |
| 4 | 0.162456 | 0.391596 | 0.011524 | 0.839135 | 0.139856 | 0.106626 | 0.123465 | 0.084361 | 0.223769 | 0.112332 |
| 5 | 0.060349 | 0.190175 | 0.063550 | 0.950873 | 0.072900 | 0.063582 | 0.079430 | 0.079461 | 0.158479 | 0.069984 |
| 6 | 0.114089 | 0.284654 | 0.159691 | 0.853961 | 0.142327 | 0.097124 | 0.154055 | 0.159805 | 0.227723 | 0.142782 |
| 7 | 0.016251 | 0.160905 | 0.013065 | 0.965427 | 0.070798 | 0.022720 | 0.080645 | 0.080678 | 0.128724 | 0.080710 |
| 8 | 0.194970 | 0.295880 | 0.202834 | 0.778632 | 0.194658 | 0.156194 | 0.156194 | 0.117418 | 0.311453 | 0.171922 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 9 | 0.036514 | 0.289216 | 0.144970 | 0.723040 | 0.361520 | 0.202813 | 0.166733 | 0.174036 | 0.368751 | 0.072955 |

A specialized normalization model is presented in Table 6, where data from such factors as air temperature, relative humidity and leaf moisture, soil temperature, radiation, wind speed were included.

Table 6. Custom Model

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.016124 | 0.159647 | 0.032121 | 0.957879 | 0.070244 | 0.057664 | 0.095980 | 0.092819 | 0.159647 | 0.064146 | 0.018750 | 0.082031 | 0.017578 | 0.019922 | 0.996088 | 0.004687 |
| 1 | 0.068066 | 0.058231 | 0.064863 | 0.970519 | 0.071171 | 0.019604 | 0.094043 | 0.048785 | 0.152048 | 0.077900 | 0.013054 | 0.054520 | 0.012286 | 0.013822 | 0.998249 | 0.003839 |
| 2 | 0.071505 | 0.003244 | 0.100737 | 0.973300 | 0.064887 | 0.068326 | 0.084547 | 0.078091 | 0.113552 | 0.048957 | 0.023159 | 0.083372 | 0.017369 | 0.022001 | 0.995831 | 0.006948 |
| 3 | 0.230647 | 0.736892 | 0.258373 | 0.230279 | 0.046056 | 0.147931 | 0.276887 | 0.212501 | 0.322390 | 0.185052 | 0.021014 | 0.088482 | 0.017696 | 0.022121 | 0.995423 | 0.007742 |
| 4 | 0.162456 | 0.391596 | 0.011524 | 0.839135 | 0.139856 | 0.106626 | 0.123465 | 0.084361 | 0.223769 | 0.112332 | 0.023722 | 0.077097 | 0.016605 | 0.021350 | 0.996329 | 0.009489 |
| 5 | 0.060349 | 0.190175 | 0.063550 | 0.950873 | 0.072900 | 0.063582 | 0.079430 | 0.079461 | 0.158479 | 0.069984 | 0.019278 | 0.082466 | 0.016065 | 0.020349 | 0.996023 | 0.009639 |
| 6 | 0.114089 | 0.284654 | 0.159691 | 0.853961 | 0.142327 | 0.097124 | 0.154055 | 0.159805 | 0.227723 | 0.142782 | 0.021261 | 0.083926 | 0.014547 | 0.020142 | 0.995920 | 0.005595 |
| 7 | 0.016251 | 0.160905 | 0.013065 | 0.965427 | 0.070798 | 0.022720 | 0.080645 | 0.080678 | 0.128724 | 0.080710 | 0.023261 | 0.069784 | 0.015508 | 0.021046 | 0.996918 | 0.007754 |
| 8 | 0.194970 | 0.295880 | 0.202834 | 0.778632 | 0.194658 | 0.156194 | 0.156194 | 0.117418 | 0.311453 | 0.171922 | 0.018402 | 0.084431 | 0.017319 | 0.021649 | 0.995852 | 0.006495 |
| 9 | 0.036514 | 0.289216 | 0.144970 | 0.723040 | 0.361520 | 0.202813 | 0.166733 | 0.174036 | 0.368751 | 0.072955 | 0.019710 | 0.077745 | 0.016425 | 0.018615 | 0.996454 | 0.005475 |

Normalized data for the striped bread flea obtained by using the *normalize()* function. This data is already ready for training. The training of the obtained data will be carried out in the next research. Thus, we have obtained the results of normalization.

After normalization, all numeric values in the input features are moved to the same area of change (a certain narrow range). This combines them into one machine learning model and guarantees the correct operation of computational algorithms. For clarity, Figure 1 shows a graph of normalized upper and lower data of a bread striped flea.

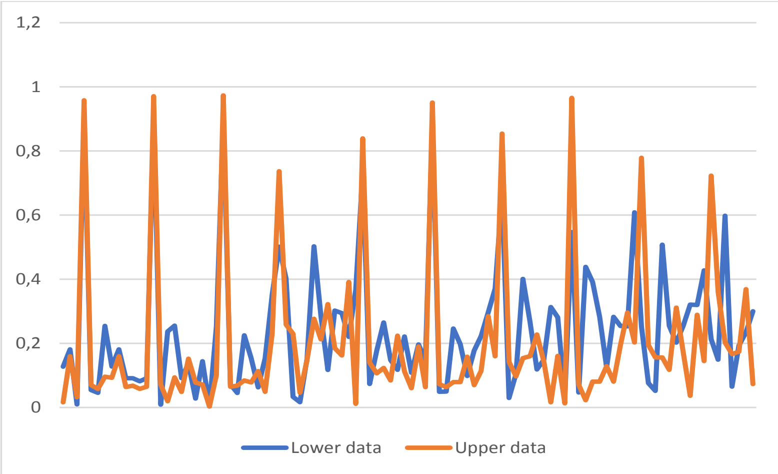


Fig.1. Normalized data in the range [0..1]

**Discussion**

When applying the lower bounds from Table 2, the normalized data from Table 4 is larger than from Table 3, where we took the upper data and got the normalized data from Table 5. That is, the lower the input data, we get a larger normalized data.

Normalization plays an important role for further research in network training. All pest detection data is ready, that is, it is normalized and ready for training in a neural network. Data normalization generally speeds up training and results in faster convergence. Normalizing the input data according to certain criteria before the training process is crucial for getting good results, as well as for significantly speeding up calculations. Agricultural research has profited from technological advances such as data mining, automation.

**Conclusion**

So, to achieve the goal is to determine the factors and indicators for the normalization of input data, for use in predicting the growth dynamics of the striped flea on the basis of an analytical system to increase productivity. Such tasks were implemented as in the first task: identifying factors and collecting numerical data to identify the pest, which will serve as data for machine learning. We collected data, identified the main factors for the detection of the striped bread flea. The fields of Northern Kazakhstan were studied from 2011 to 2021 and the results are shown in Table 1. The second task was to normalize the collected data for use in neural network training. Of all the collected data, the normalization indicated in Tables 3-6 was described and carried out.

As a result, the goal of the research was achieved and optimal normalized data were obtained for further training data in a neural network to predict the pest population. The continuation of this research will be work on creating a neural network model.

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