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Increasing the efficiency of warehouse analysis using artificial intelligence

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Abstract: Logistics in companies is a necessary process that has high costs with mostly no added value. Lowering this cost is vitally important for companies to stay competitive. Nowadays, storage systems are a critical part of any company's logistic system, and many of them try to reach an optimum level where they can operate with little freedom of movement of goods declared by the changing market. There are several manual and automated methods to achieve this. However, we hear quite little about the use of artificial intelligence in the field. This study focuses on the implementation of AI technology into warehousing, especially in categorizing goods. After an overview of the recent literature on AI technologies and their application in the field of logistics, the introduction of an AI application follows. The main goal of the application is to categorize each good stored in a warehouse into ABC-XYZ groups, which determines the place of the good in the warehouse and the ordering frequency with the quantity. After acquiring and cleaning the training data from a real company, the determination and selection of the least input parameters is an important and challenging task, which is demonstrated. The effectiveness of the supervised learning can be seen as an ANN (artificial neural network) can output, with the aid of a non-conventional metaheuristic approach - the black hole algorithm - as the learning agent is demonstrated by an example, which also shows the result of an ABC-XYZ categorization run on a dataset from a multinational company.

1 Introduction and literature review

Recently, as we can see in the news, there has been a surge in the development and use of artificial intelligence (AI), not only in research and industry, but also active use in real life situations. So far, large corporations have used some forms of AI to determine the weather [1], to analyse compounds and tissues chemically and biologically [2], to trade stocks [3], to assess consumer needs [4], to create tailored advertising [5] or to run the largest text search systems [6], to name just the most well-known ones. Apart from the last decade, there has been mass-fear about the effect, power and awakening of artificial intelligence [7], which has been greatly influenced by the exaggerated media, but nowadays AI is mostly accepted as a useful tool that, if used properly, can do no harm. To give a concrete example, the open source chatbot ChatGPT is enjoying unprecedented popularity, with 13 million daily users and a total user base of 110 million in January 2023 [8]. It can engage in quasi-intelligent safe conversations, grant answers, and help on topics or write your homework, which has caused huge scandal in the US.

Considering this, it is hard to imagine that there are industrial areas where artificial intelligence is hardly used at all, neither in the design, nor in the construction, nor in the operational phases, although it is also mentioned in the Industry 4.0 principles and directions under the topic of automation [9,10].

Most researchers agree that automation and Industry 4.0 tools not only allow us to improve our hardware, but also to automate our software and decision-making systems [11]. To achieve this, existing enterprise databases, such as SQL-based ones, can be easily linked to program written in C#, .Net or MATLAB languages and run AI supported queries on them continuously to find hidden parameter or process relationships [12]. This could easily lead to IoT-SL (Internet of Things - Smart Logistics) systems, where smart contracts and more effective services can increase warehouse efficiency, faster receipt actions, issuing, transferring, and picking [13]. One of the biggest and most advanced areas of artificial intelligence research is image processing, which is essential for self-driving vehicles and visual recognition systems. To train these systems, large amounts of data are needed, and if we want to continuously expand this data, we need to use cloud-based services. EDGE computing with AI-infused cloud services provides a solution for this problem [14].

In a warehouse, there are plenty of possibilities to use AI-driven or augmented systems. As I mentioned earlier visual recognition is in a very advanced state, which can be used to control safely fully autonomous vehicles [15]. Visual recognition and artificial intelligence have another big impact on warehousing within sorting and picking. Pick-by-vision owes its existence to smart glasses and the rise of augmented reality [16]. Although not yet widely adopted due to its relatively high installation cost and AI training time, but in the future, it could easily become more accessible [17]. As most of us know, pick-by-voice is a well-established technology, that can work without any major AI, but for better voice recognition or giving special instructions the method can be improved by AI [18].

Another unique example of the implementation of AI into warehouses comes from researcher Min-Chun Yu, with a great promise to compare the outcome of the original ABC analysis with methods infused by artificial intelligence [19]. The ABC analysis has a few variations, but most of them sorts the stored items in descending order by price multiplied by quantity of consumption, then using the Pareto principle to classify them into categories A-B-C with 80-15-5% breakdown. A set of data provided as training and testing data for the three method of AI, which are: Back-Propagation Network (BPN), which is a type of Artificial Neural Network (ANN) and use a back-to-front normalising method for setting the weights of the node connections; Support Vector Machine (SVM), where minimal risk structures can be achieved by a linear model, and implementing vectors as margins of parameters; and k-nearest neighbours, which is a reliable clustering tool, that can be used for easy and fast grouping, but very sensitive for input and initial data. The study claims, that the SVM method worked the best, on average the model guesses the right categories with a success rate of nearly 80%. This study has inspired this research most. Recently real company data was received for optimization and research purposes, that could easily be used to create an ABC analysis dataset for AI testing and validating. The company also performs their own XYZ analysis on items, with which they can store more effectively and calculate shipping quantities better, thus improving their material flow and make a more efficient warehouse and logistic system.

This paper's purpose to create an example of training a weak AI, that can pre-categorize items based on a corporate supervised data set into both ABC and XYZ categories.

2 How artificial neural networks works?

Most of the time for categorizing tasks we don't need a very powerful or complicated AI models. Most logistic based problems are not a particularly complicated for this kind of tools: most of the time it doesn't need visual processing or text recognition with a human like response. In most cases there are a fixed number of parameters for inputs, and well-defined outputs. There are plenty of artificial models and techniques which we can use to solve this problem. One of the easiest, well described, and well-developed models are the Artificial Neural Networks (ANN). These are machine learning models, that are designed to simulate the way human brain works, where nonlinear classifiers mostly used to create and refine complex relationships between inputs and outputs for classification purposes. An ANN model contains several node-layers for processing information, called neurons. The layers are usually called input layer, hidden layer and output layer. ANN models can be used for a wide range of tasks, of which the best known for image and speech recognition or natural language processing. ANN models are trained on supervised data with the help of heuristics, or a process called backpropagation, where the algorithm adjusts the weights between neurons in response to the input data. This process iterates until the model is able to accurately predict the output for a given input in the test data. However, this process can also be computationally intensive and for complex problems, which is not always predictable, or require significant amounts of training data. After the learning phase the model can be used with a high degree of certainty on actual data that has not yet been seen to give a proper output [20,21].

Backpropagation is a very powerful and tool for adjusting the weights of connections between nodes, but not the only one; we can also use heuristics for this purpose. The former is a simple and efficient techniques, that best at smaller standardized problems in matrix forms and fine-tuning already good solutions, but not so efficient in big complex and noisy datasets. It is also very sensitive for the initial settings and input parameters [22].

The heuristic approach is another good technique to adjust the weights, but it requires more computing power and the solution's correctness has a bit more uncertainty. It is good for any kind of problem, mostly without restriction, and with their application, it is possible to oversee a much larger spectrum of weight-solutions [23]. Most of the times when we search for heuristics in AI topics the genetic algorithm (GA) will dominate our findings. This method is a very good candidate for almost every problem including weight adjustments in ANN models, because it is very robust, easily calibrated, and have numerous versions included as packages in many programming languages and compliers. Genetic algorithm, however, is not the only good heuristic option. There are many cases, where other heuristics can surpass GA in different tasks, like in the paper "Black Hole Algorithm and Its Applications" [24]. The black hole algorithm (BHA) is a population-based metaheuristic algorithm with a semi-memory storage for solutions. Classification is the strength of this algorithm, which can work very effectively when the parameters are fractional numbers with limits, where we can interpret the "distance" between individual objectively [25]. In most ANN the numbers and their weights are predetermined and limited (-1…1), which is ideal for the BHA to work effectively. In addition to these, the basic algorithm of BHA is much simpler and works with much fewer steps than GA, so an iteration step is only a fraction of the time of GA. It also handles more populations more effectively because an iteration step doesn't require ranking or weighting the individuals, there are no special crossovers, only the best remains and the rest of the population changes. These are the reasons why BHA was chosen as the artificial neural network's weight calibrating tool, for the ABC-XYZ classification problem.

3 ANN model for ABC-XYZ prediction with black hole algorithm

To create a practical/industrial acceptable ANN model, two initial steps must be taken: data mining and layer (parameter) definition. The order of these is determined by whether we already have the data for testing that can be processed, or whether we are trying to create a new system and data collection will follow. In this specific case the access to corporate data was very useful, which is used as a test database after cleaning and pre-processing. Naturally, permission was granted by the company to use their data in this research if the company and the goods cannot be recognized by competitors. This means the data collection came first and the definition of layers were the second step. There is only rule of thumb on how many hidden layers there must be (1 is always required): for not too complex tasks (with reasonable parameter count) most authors recommend between 1 and 3. The same applies to the number of neurons (or nodes) in the hidden layers: there are formulas, but since the number of parameters can be between a few and millions (image processing) it's very task dependent. For a small number (under 100) of input parameters the first hidden layer has a node count of maximum twice the number of input and output parameters; the second hidden layer and after, the neuron counts should be between 2/3 and 1/2 of the previous layer [26].

After cleaning and processing the corporate data 9 inputs were selected, and of course 2 outputs: prediction of item classification into: ABC & XYZ. Because these are not high numbers, and from my understanding, this problem didn't look very complex, so I created 2 hidden layers with 12 and 6 nodes. These parameters and layers can be seen in Figure 1.

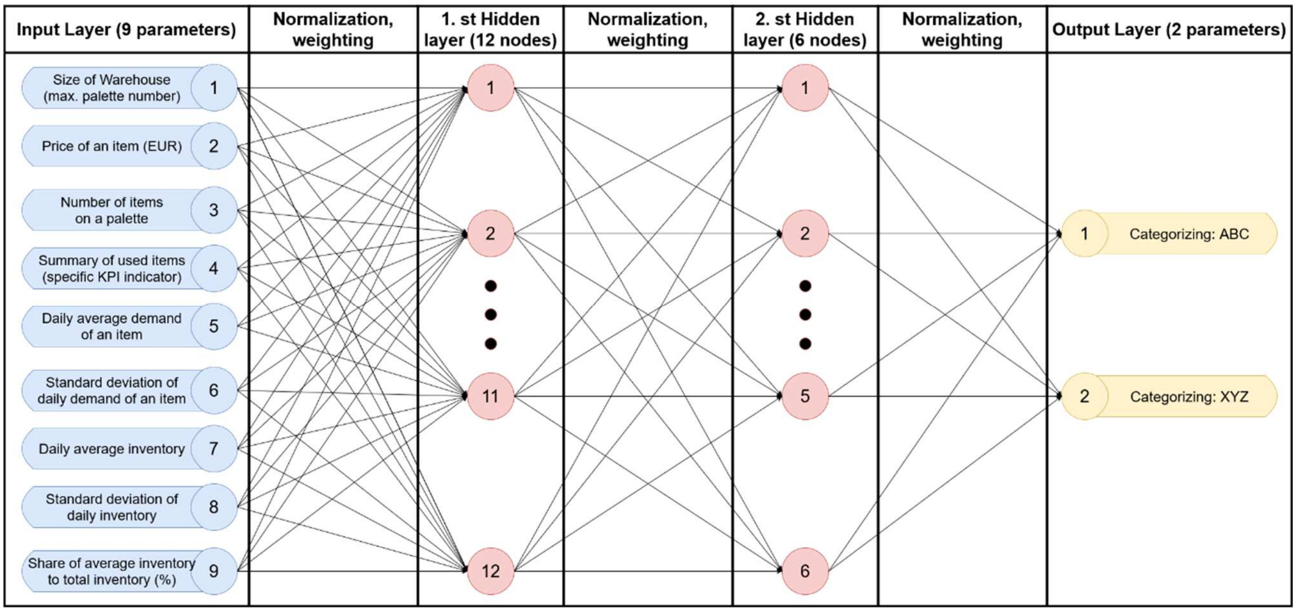

Figure 1 Layers of ANN network for ABC-XYZ prediction

3.1 Defining the input dataset for artificial neural network

Besides cleaning, pre-processing the data is almost always needed. If the whole cleaned dataset was given as input we had nearly 140 parameters (in daily breakdown), which is unnecessary. Input parameters 1…4 is not changed, these are the followings: size of warehouse (capacity by palette number of the location), price of an item in EUR, number of items in a palette, and a KPI indicator, which summarizes the number of used items (only left it in because it has been asked by the company). Input parameters 5…9 is calculated: daily average demand of an item, and its standard deviation, daily average inventory and its standard deviation, and the average of the daily percentage of an item occupancy in the given warehouse. With these inputs, we need to try to avoid having data that are part of other parameters or to express them by the relationships of other parameters. Always aim for the previous principle if effectiveness is the goal. The only exception is we have parameters that, although related, have a very complex relationship that can only be truly expressed through more layers that we have.

The corporate dataset contained information about nearly 3200 items, which was real storage and movement data for a whole month from multiple company warehouses broken down to the second. Unfortunately, about 1800 of the 3200 items were not active in the examined month, so more than half of the training data we lose by default. In addition, there were errors and gaps in the remaining dataset: there were some warehouses that doesn't classified items into ABC-XYZ, and most items had at least one parameter missing, like price or quantity. After the data cleaning only 255 items remained in the training dataset, which is still plenty enough to train an AI. Part of this cleaned and pre-processed data set is shown in Table 2.

In Table 1. we can see two yellow column ABC (Corp.) and XYZ (Corp.). These are the classifications defined by the company for every item in the testing dataset, and most importantly for AI developers, these are the supervised outputs, that we want to acquire at the end of the training process. Also, the green columns in the table are the input parameters and the grey columns (120 columns) contains the daily data, which used for the calculation of input parameters 5…9.

Table 1 Part of training dataset

Item no.	Warehouse size (palette)	Price of item (EUR)	Number of item on palette	Used palette number of item (KPI)	Daily average demand (palette)	SD of daily average demand (palette)	Daily average inventory (palette)	SD of daily average inventory (palette)	Average daily stock ratio	ABC (Corp.)	XYZ (Corp.)	Initial stock factory total (no. items)	Initial stock factory total (palette)	Income (no. item)	Used items (no. item)	Remains (no. item)	Stock (palette)
														03.25.2022	03.25.2022	03.25.2022	03.25.2022
N1	1155	258.46	24.00	6.83	23.43	9.22	58.43	15.34	0.0506	A	X	2208	92	0	552	1656	69
N2	1155	169.96	48.00	1.71	11.71	6.80	26.71	28.16	0.0231	A	Y	624	13	0	480	144	3
N3	1155	100.52	32.00	6.25	28.57	14.33	133.57	51.17	0.1156	A	Y	8224	257	0	1312	6912	216
N4	899	48.33	80.00	1.54	17.57	7.16	40.86	22.81	0.0454	A	X	2000	25	0	1760	240	3
N5	899	40.70	105.00	0.50	7.43	3.69	11.00	7.55	0.0122	A	X	945	9	945	945	945	9
N6	899	48.32	64.00	1.48	13.57	8.44	4.29	11.95	0.0048	A	Y	704	11	0	1344	-640	-10
N7	899	25.30	36.00	4.53	23.29	11.16	41.29	11.18	0.0459	A	X	2124	59	864	1116	1872	52
N8	1155	23.83	80.00	0.94	10.71	5.56	38.71	12.54	0.0335	A	Y	3680	46	0	1280	2400	30
N9	899	50.07	48.00	0.85	5.86	5.70	31.71	11.29	0.0353	A	Y	624	13	384	0	1008	21
N10	1155	25.89	48.00	1.69	11.57	5.44	42.43	22.71	0.0367	A	X	1152	24	0	480	672	14
N11	1155	137.22	48.00	0.23	1.57	2.07	3.86	3.02	0.0033	A	Y	288	6	0	0	288	6
N12	1155	21.50	50.00	0.72	5.14	9.25	74.29	24.74	0.0643	A	Y	1700	34	1700	1150	2250	45
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

3.2 The importance of ABC and XYZ analysis

The results of ABC and XYZ analysis are not the most important indicators or management parameters for the company, but they can be used as an easy decision support tool for the whole internal and external logistic system to manage the stock levels of incoming materials and items in the warehouses, plan stock entries and withdrawals, free up space, control delivery deadlines, prepare the right materials for product changes and plan the ordering quantities coming into and out of the factory with their time intervals.

ABC analysis aims to distinguish between items (mainly materials) that are significant and insignificant to the materials management system. It separates the essential from the non-essential based on the annual use (value and/or quantity) of the products, classifying them into 3 categories (A, B, C). The materials are grouped according to their relative importance and differentiated inventory management methods are applied according to the groups [27].

The pareto principle states: about 5-20% of the items cover 70-80% of sales these are "A" category items. "B" category items cover 20-30% of sales with 20-30% of sales and the remainder being "C" category. Pareto logic also states: the biggest savings can be achieved with "A" category because of its high value. This is certainly true because of the law of large numbers, but the other categories should not be forgotten, as "C" will be precisely those products that are sold infrequently and in small quantities. [27].

The results of XYZ analysis are to indicate and categorize the fluctuations in demand for items over a longer period. We can express market volatility in terms of the relative dispersion of demand. The "X" category includes those items whose consumption shows only minor fluctuations. This category is characterised by a high level of forecasting. The use of materials in category "Y" is more volatile, but there is a certain tendency to fluctuate. For example, there may be a steady increase or a steady decrease, or perhaps seasonal patterns of use. This category is characterised by a medium forecast accuracy. Category "Z" includes materials whose use is completely irregular, with a very low forecast accuracy [28].

4 Application and results

There are many programming languages and compilers that can write ANNs effectively, but for research purposes, there is a very simple and effective programming language and its application that handles matrices very well, which is MATLAB. There was no doubt that the application was written in this language. Also programming in MATLAB was fairly easy with the pre-made libraries and the huge number of blogs on the internet was helpful in this topic. In addition, the implementation of the black hole algorithm, which is the core process of the model, was also relatively simple, because of its easy structure and comprehensibility. After a few unsuccessful runs, when the results did not improve, the solution was able to move forward with a simple trick: make the output neuron thresholds a variable. Previously, we had defined the values and the categories, when the first output neuron's value is between 0…0.33 was category "A", between 0.33…0.67 was category "B", and above 0.67 was category "C". This applied to the XYZ category also. After making the limits their own parameters, which can be modified by the BHA, the results improved significantly.

Figure 2 shows a complete run of the current best result of ABC-XYZ solutions. The run lasted around 9 hours on a currently very average computer (HexaCore AMD Ryzen 5 3600 CPU with 16GB DDR4 memory and NVIDIA GeForce GTX 1660 SUPER 6 GB video card). During this time, roughly 25000 iterations were performed with a population of 500.

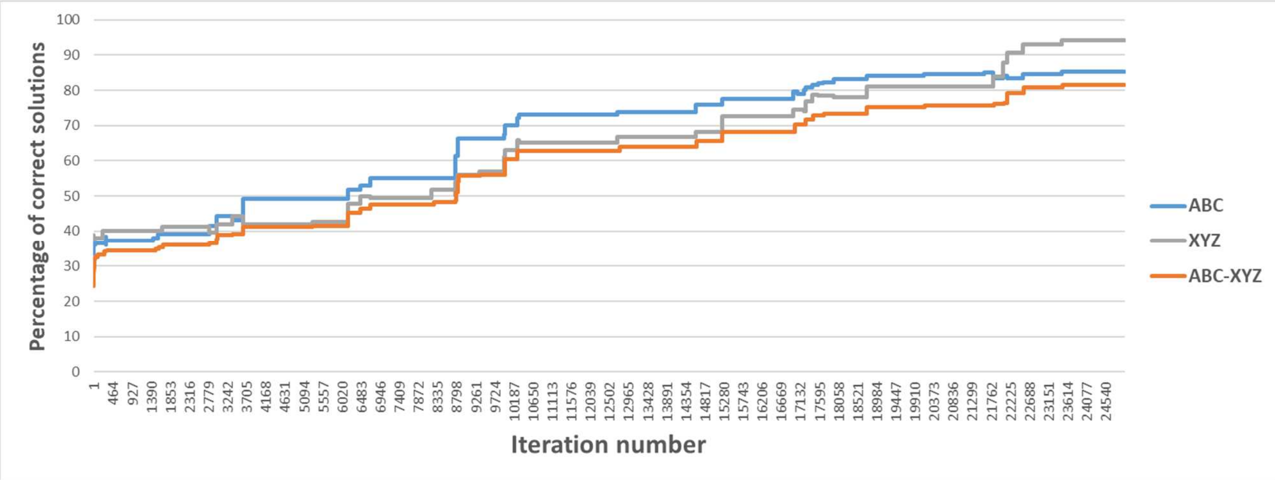

Figure 2 Result of an ANN performance for ABC-XYZ prediction

As Figure 2 shows the ABC-XYZ results starts at around 25% of good predictions of the 255 training data, which is statistically correct: there are around 40% of "C" category and 40% of "Z" category items. To predict only this category, which is the largest, there is a near 16% of correctness, just by categorizing every item into "C" and "Z". After the initial categorization there is a quick improvement: in only 9000 iteration the model guesses the categories correctly 50% of the time. After the 25000 iterations, the model can categorize the training items into ABC category 85%, XYZ category 93% and both 82% correctly. This level is higher, than a normally skilled worker capable of, if he/she needs to categorize an item based only the item's parameters, and without seeing the other item's values. It is likely that if the application had more runtime, than the results could have gotten better results, and after a while it could have reached practically 100% accuracy, but given the slowing improvement, this task could have taken several days or even a week on this computer.

5 Conclusions

The usage of artificial intelligence in the field of internal logistics is rare, besides visual recognition in AGV and robotic systems, which can be also recognised from, the literature review. There are only a few literatures, which encourage the industry to implement high-level systems that support Industry 4.0 principles with AI-implementation, with which companies are much capable of making simpler decisions or assisting the logistics systems. These are both visual and background assistance benefits, mainly for easy transparency, flexibility, and easy management of materials and goods, and there are plenty of un-used databases that, can be a source for training data. The only literature, that can be found on the topic of this research is from Min-Chun Yu, who uses Artificial Intelligence to create a method for automatic categorization of warehouse goods into ABC. The ABC categorization is good for representing the quantities of certain items in the system, but doesn't show us the frequency of usage, which is also important to create a stable and optimal warehouse and manufacturing system. This research attempts to address this scientific gap in an unconventional way, by using an artificial neural network, to categorize each item of a given company into both ABC and XYZ categories, based on their own manual categorization. In most cases, such categorization manually will only give good results if you have had the item for a long time and have enough data about it. Another advantage of the AI-trained method is that the trained method does not need the data mentioned above. It can immediately categories it with high accuracy, provided that the training was successful and appropriate parameters are available. A properly trained system can also handle faulty or incomplete items (parameters) to a certain extent, which increases the robustness of the system.

To prove the useability of the AI aided systems, an application was created in MATLAB, with the learning black hole optimization algorithm (substitute for the genetic algorithm and backpropagation, which are commonly used for this purpose), that the method can predict an item category correctly 82% of the time after an 8-hour running on an average computer. This can be improved by giving more runtime to the method or combine multiple algorithms to make it more efficient. In average this 82% is as good as an average human workers guess with some experience in the field of warehousing and logistics.

Future of this research: further testing of this model and an investigation on data from other companies, with these settings, to see the results and percentages of correctness. In addition, these questions should be answered in the future: Can we create a model and a set of rules consisting pre-determined weights, which will create good results with industrially accepted and collectable pre-defined inputs? Does the black hole algorithm aided AIs performed better, than a Genetic algorithm or backpropagation aided artificial neural networks?

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Review process

Single-blind peer review process.