High-performance information technology for processing large datasets and biomedical images to improve the accuracy of computer-aided decision support systems

Oleksandr Poplavskyi[a*], Sergiy Pavlov[b], Valerii Denysiuk[b], Svitlana Belinska[c], Iryna Shvarts[b], Olga Akimova[d], Oleksandr Kornilenko[b], Marta Tarczyńska[e], Krzysztof Gawęda[e], Ainur Kozbakova[f], Andrzej Smolarz[g]
[a]Kyiv National University of Construction and Architecture, 31 Povitroflotskyi Ave, Kyiv, Ukraine, [b]Vinnytsia National Technical University, 95 Khmelnytske Shose, Vinnytsia, Ukraine; [c]State University of Trade and Economics, Department Commodity Science and Pharmacy, Kyoto Str.,19, 02156, Kyiv; [d]Vinnytsia Mykhailo Kotsiubynskyi State Pedagogical University,Vinnytsia, Ukraine; ; [e]Arthros Med Ctr, Chodzki 31 St, PL-20090 Lublin, Poland; [f]Institute of Information and Computational Technologies CS MSHE RK, Almaty, Kazakhstan; [g]Lublin University of Technology, Nadbystrzycka 38A, 20-618 Lublin, Poland;

ABSTRACT

Modern biomedical engineering is characterized by the rapid growth of data volumes that require processing and analysis to support clinical decision-making. Information technology plays a key role in ensuring the high-performance processing of these large datasets, contributing to the increased accuracy and speed of clinical diagnoses, as well as more effective subsequent patient treatment. This article aims to review current approaches and technologies used for biomedical data processing and to rethink the approach to using big data in decision support systems. Special attention is given to machine learning methods that enhance data analysis efficiency. The data processing approach proposed in this article allows for an 10-12% increase in the accuracy of spinal pathology classification, confirming its feasibility in medical practice.

Keywords: big data, biomedical engineering, intelligent decision support systems, machine learning, pathology classification, high performance

1. INTRODUCTION

Begin the Introduction two lines below the Keywords. The manuscript should not have headers, footers, or page numbers. It should be in a one-column format. References should be listed at the end of the manuscript and numbered consecutively in the order of their citation in the text. In-text citations can use superscript or bracketed reference numbers

The contemporary advancement of computing technology is characterized by a continuous increase in its capabilities, leading to an exponential growth in the volume of data that can be processed. Notably, the enhancement in computer system performance allows for the storage and analysis of large biomedical data sets with unprecedented speed and accuracy[1]. This, in turn, compels researchers to constantly seek new methods and models for information processing, adapting information technologies to meet new requirements and opportunities.

Over the past decade, neural networks have gained significant prominence, particularly for processing visual information. Neural networks, with their ability to learn and adapt to complex data structures, have become a crucial tool in the scientific community, finding extensive practical applications[2]. Consequently, most companies and researchers are focused on modifying neural network architectures, tuning hyperparameters, and improving the quality of input data. These approaches significantly enhance the accuracy, speed, and quality of data processing, which is critical for information technologies.

Currently, there is an extensive body of scientific literature exploring various aspects of neural network optimization.

*e-mail: apoplavskyi@gmail.com

Photonics Applications in Astronomy, Communications, Industry, and High Energy Physics Experiments 2024, edited by Ryszard S. Romaniuk, Andrzej Smolarz, Waldemar Wójcik, Proc. of SPIE
Vol. 13400, 134000E · © 2024 SPIE · 0277-786X · doi: 10.1117/12.3057444

Researchers are developing new architectures, refining training methods, and experimenting with different data sets to achieve better results[3]. Meanwhile, classical information processing methods, which were widely used previously, have fallen behind the competition with newer technologies and have taken a back seat.

This article aims to demonstrate how the symbiosis of classical information processing methods and modern technologies, particularly neural networks, can improve data analysis results in computer-based decision support systems. Applying this approach allows for combining the advantages of both methods, ensuring more efficient information processing and enhancing the accuracy of pathology classification using a single data set. The research findings confirm the feasibility of such approaches for achieving better results in intelligent decision support systems.

2. ALGORITHM FOR AN AUTOMATED SPINAL DISEASE CLASSIFICATION SYSTEM

Modern methods for processing large medical databases increasingly utilize neural network techniques, which demonstrate high efficiency in identifying complex interrelationships within the data. An essential stage in the development of such systems is the thorough analysis and preparation of input data. It is crucial to cleanse the data of anomalies and irrelevant information that could negatively impact the analysis results.

A successful implementation example can be the architecture of a convolutional neural network (CNN), which is trained on well-prepared large datasets[4]. In this case, training the model involves optimizing the weight coefficients to minimize the discrepancy between the model's predictions and the actual class labels. The training process concludes with testing the model on new data to evaluate its accuracy and effectiveness.

In this algorithm, key factors include the choice of neural network architecture, the configuration of training parameters, and the quality of the input data.

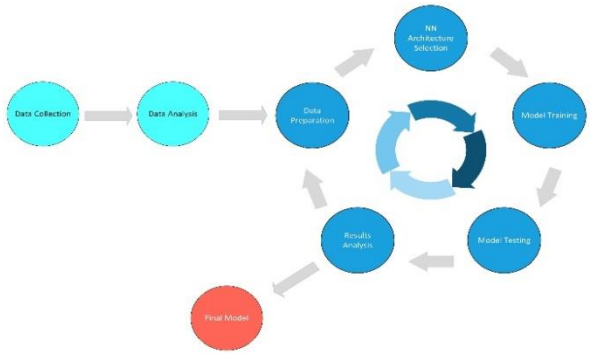


Figure 1. Diagram of the Creation of an Automated High-Performance System for Processing Large Volumes of Biomedical Data for Disease Classification Based on Neural Networks

For image classification, a convolutional neural network (CNN) can be utilized, which consists of several types of layers. The convolutional layer applies filters to perform convolution operations, allowing the scanning of the input image and generating activation maps that contain all detected features. The pooling layer is used to downsample the features after the convolutional layer, applying either maximum or average pooling. The fully connected layer processes the flattened input, where each input is connected to all neurons, allowing the connection of hidden layers to the output layer and optimizing class scores. The combination of these layers in a CNN provides effective feature extraction, downsampling, and classification of image features, enhancing the accuracy of classification.

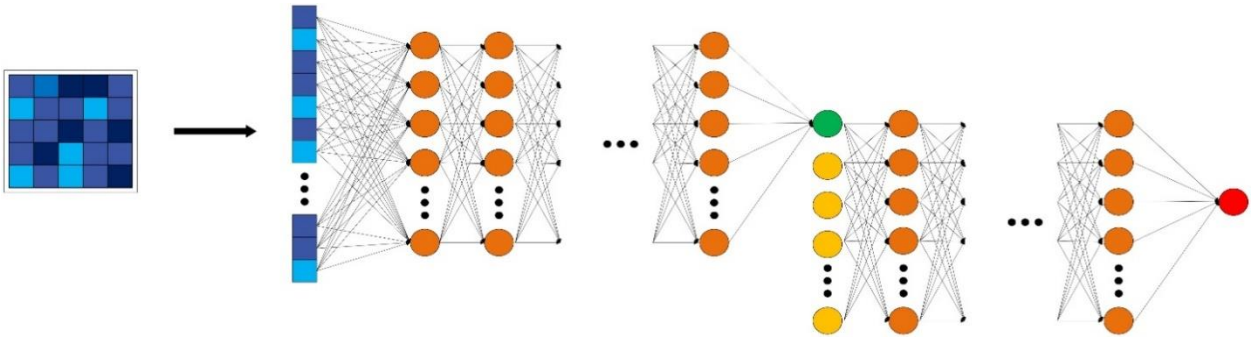


Figure 2. Modification of the Fully Connected Layer in the Output of a Convolutional Neural Network (CNN)

Model training is conducted based on a pre-defined dataset, which includes images with corresponding labels, using an iterative approach. The use of the Adam optimizer and the CrossEntropyLoss function allows for efficient updating of the model's weights. The testing process involves processing images from the test dataset to obtain predictions about patients' health conditions, enabling the assessment of the model's accuracy.

In the context of this study, special attention was given to the extraction of texture features[5] from the images contained in the dataset. This approach involved collecting a large number of texture features, contributing to a comprehensive description of the images' geometric characteristics. The extraction of features such as the coefficient of asymmetry and the area of asymmetry, among others[6,7], provided the capability to accurately classify and analyze images for pathological changes.

The application of neural networks, combined with texture feature analysis data, allowed for efficient handling of large data volumes. This synergy of methods facilitated a deep analysis of the data and the identification of more complex, indirect dependencies that are crucial for pathology identification. The neural network architecture, developed based on the extracted features, ensured the model's ability to timely and accurately recognize key disease indicators. This was made possible through a detailed process of training and texture feature analysis.

3. RESULTS OF EXPERIMENTAL MEASUREMENTS AND CLASSIFICATIONS OF SPINAL PATHOLOGIES IN AN AUTOMATED SYSTEM

The methodology of conducting experimental research is crucial for any scientific investigation, as it underpins the validity and reliability of the obtained results. In this study, the methodology focused on evaluating the effectiveness and reliability of the developed methods and tools, as well as the final model of the proposed approach. The validation of the developed methods on fundamentally different large data sets, both graphical and statistical, is essential for confirming their universality and the reliability of the results[8,9,10].

In this context, the application of the technology to graphical data, encompassing series of images, requires the analysis of complex visual relationships and patterns. This includes object recognition, texture processing, and the analysis of colors and shapes. On the other hand, statistical data, which in this study consist of numerical records-tables with 24 previously extracted quantitative data points for each image, such as autocorrelation, contrast, entropy, and the coefficient of asymmetry[5] and others, were also used. Conducting experiments on such diverse data sets allows not only to test the universality of the developed methods but also to ensure their reliability under different conditions and for different types of data[11,12].

The initial stage of the research involved data processing using a convolutional neural network (CNN), aimed at extracting important characteristics from thermographic images of the human back for spinal pathology classification. This process entailed several key steps, each contributing to the preparation and processing of data for subsequent deep learning. The Pandas library was used for data loading and manipulation, providing a wide range of functionality for reading data from various file formats, including dataset imports. For image preparation for further analysis, the Pillow (PIL) library was used, allowing for opening, manipulating, and saving images. In this study, the Pillow library was applied to convert images to RGB format, necessary for the correct operation of convolutional neural networks that require images in a standard color format[13,14].

The process of splitting data into training and test sets included the use of the train_test_split function from the Scikit-learn library, which allows for automatic data distribution according to specified proportions. In the study, indices were used to split the dataset, with the first 90% of the data assigned to the training set, and the remaining 10% to the test set. This approach is a certain standard that ensures balanced model training and its adequate evaluation on new data.

Applying transformations to images before network training helped to increase the effectiveness of training by reducing the risk of overfitting and enhancing the model's robustness to input data variations. The study used standard transformations from the Torchvision library, including converting images to tensors and their normalization, which is a standard practice in deep learning[12,15].

The developed CNN model, SimpleCNN, a classic example of a convolutional neural network, included several convolutional layers and fully connected layers, allowing for effective image processing. The first convolutional layer used 16 filters of size 5x5 with padding 2, followed by a pooling layer that reduced the dimensionality of the input data. The second convolutional layer, also with 32 filters, further reduced the dimensionality, preparing the data for the fully connected layers, which transformed the feature vector into final classification labels.

The model was trained on the training data set using the Adam optimizer and CrossEntropyLoss function, ensuring error minimization during classification. The training was conducted over 20 epochs, with continuous monitoring and control of losses to prevent network overfitting. After training, the model was evaluated on the test data set, where classification accuracy was measured by comparing predicted labels with actual ones.

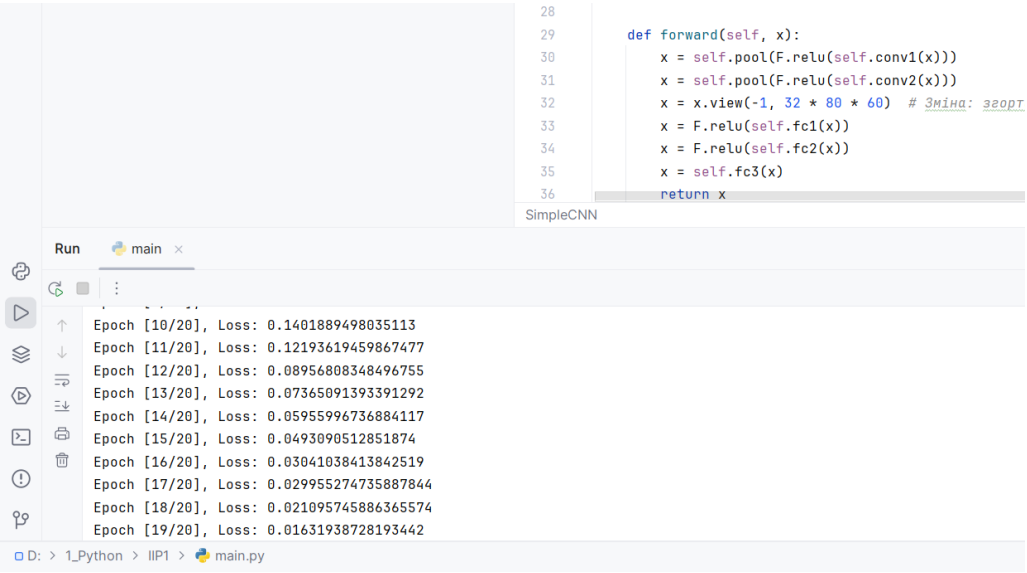


Figure 3. Loss Monitoring During Convolutional Neural Network Training

The results obtained from the CNN model were used as input data for the proposed architecture (Fig. 2). This data, containing information about the probabilities of spinal disease, was further processed and stored, serving as the basis for training a more complex diagnostic model.

Constant loss monitoring during the training of the convolutional neural network was conducted to minimize losses, which indicate how well the model is learning to recognize patterns from the training dataset[9,12].

Loss monitoring during neural network training performed several functions. Firstly, it allowed for the assessment of how effectively the model was adapting to the data it was working with. A high level of loss at the beginning of training is common, but ideally, this level should decrease over time, indicating the model's increasing ability to process and classify input data accurately. Additionally, loss monitoring played a role in determining the optimal number of training epochs since too many epochs can lead to overfitting, where the model performs well on the training set but poorly on new, unseen data. This is problematic as an overfitted model loses its ability to generalize, which is unacceptable for the study.

To address overfitting, early stopping methods are typically used, where training is halted as soon as the loss on the training dataset stops decreasing or starts to increase. This method significantly reduces the risk of overfitting without sacrificing model performance[7]. However, this is not always the case. In this study, a slightly modified approach was used, which included constructing a loss diagram to find the extrema of the functions. This allowed us to determine the optimal number of training epochs for our study.

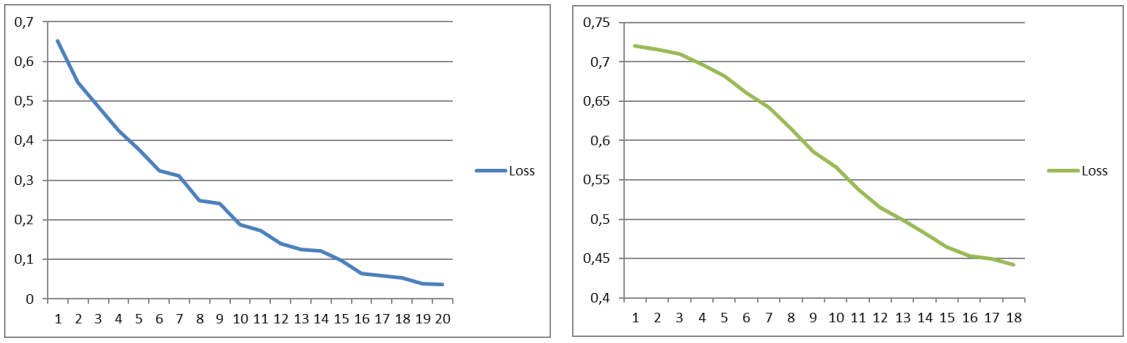
To ensure well-founded conclusions regarding the effectiveness of the proposed spinal disease classification technology, deep learning algorithms were evaluated through detailed comparison with results obtained from a classical convolutional neural network (CNN). The primary aim of this comparison was to identify the advantages of the proposed model in accurately recognizing spinal pathologies in medical thermographic images.

The classical convolutional network used as a baseline for comparison allowed for the assessment of the developed model's ability to autonomously identify diagnostically significant features without direct researcher intervention. Comparing the results of the two approaches provided valuable information on the relative effectiveness of the new model in the context of real-world data.

This comparison established that the proposed deep learning method could perform a more thorough and comprehensive analysis of medical images to identify spinal pathologies. This is achieved by integrating additional informative features and techniques that enhance classification accuracy and reduce the likelihood of erroneous diagnoses. Thus, the comparison highlighted the advantages of using this deep neural network method in medical diagnostics.

The results of processing a series of images with the classical neural network showed a gradual decrease in average loss with each training epoch, indicating the effectiveness of the training process. The initial loss of 0.695 in the first epoch indicated significant discrepancies between the model's predictions and the actual labels. However, after further training iterations, this loss value significantly decreased, reaching a minimum of 0.0586 in the twentieth epoch. This substantial reduction in loss indicates that the model better adapted to the data and improved its classification ability.

Despite the positive training dynamics, the model's accuracy on the test set was 70.59%, which may indicate certain limitations of the classical convolutional neural network in analyzing such data. The test set loss of 1.237, though higher than the training loss, still underscores the model's ability to generalize to new data, albeit with some errors.



a) b)

Figure 4. Loss Change Graph During Neural Network Training: a) Classical CNN; b) Proposed technique

The results of processing a series of images with the proposed method showed significant improvement in classification accuracy. At the initial stage of training the neural network, an accuracy of 68.26% with losses of 0.6241 was achieved, indicating effective recognition of features differentiating health conditions based on images. Over the subsequent epochs, there was a trend of decreasing losses and increasing accuracy, highlighting the model's ability to adapt and optimize its internal parameters for better data classification. During training, the model demonstrated its deep learning capabilities, with a gradual reduction in losses, emphasizing its potential in identifying complex patterns in the data.

The results of processing a series of images with the proposed method showed that the application of deep learning had a significant impact on classification accuracy. Throughout the 20 epochs of model training, there was a continuous decrease in losses, indicating effective learning and the model's ability to adapt to the data. At the final testing stage, the

classification accuracy was approximately 82.35%, with losses of 0.8819, indicating the model's high capability to differentiate between healthy and diseased patients based on their thermographic images.

Comparing these results with those of the classical convolutional neural network, where the accuracy on the test set was approximately 70.59% with losses of 1.2370, highlights an improvement of 11.76% in accuracy achieved through the implementation of the new method. Given these data, it can be concluded that the new deep learning method is a promising tool for improving the accuracy of diagnostic systems, particularly in the classification of spinal diseases.

In the detailed analysis of the data obtained in the study, additional attention was given to examining the probabilities of classifying individual images. The analysis showed that in the majority of cases where the network made correct predictions about the presence or absence of spinal diseases, it demonstrated higher (in percentage terms) confidence in its answers. On the other hand, when the network made errors, the probabilities provided were lower, indicating less confidence in these responses. This dynamic suggested the potential for further training, and consequently, a projected increase in model accuracy in the future.

This analysis is evidence that the application of deep learning can not only provide high classification accuracy but also significant prospects for improving the efficiency of diagnostic systems in medicine.

Speed Evaluation of Methods. The total classification time for a single image using the classical convolutional neural network was 0.0182 seconds, while the developed deep neural network performed the classification in 0.0207 seconds. This means that the proposed method increases the classification time by only 0.0025 seconds, which is an entirely acceptable increase for the operator. At the same time, using the proposed method allowed for an increase in classification accuracy by 11.76%. This improvement is significant and demonstrates that the slight increase in classification time is entirely justified by the substantial increase in accuracy. This makes the developed deep learning method an effective tool for improving the quality of medical diagnostics.

4. CONCLUSIONS

The process of validating the technology on various data sets revealed its universality and reliability. Specifically, it was demonstrated that the methods effectively process both graphical and statistical data, recognizing complex visual relationships and numerical indicators. The experiments confirmed the validity of the theoretical assumptions that formed the basis of the proposed technology, and showed that this technique can achieve high accuracy in prediction and classification when working with different types of data. Therefore, the developed technical solutions are effective for practical application. Based on the analysis of the experimental results, the conclusions highlight that the proposed technology can serve as a reliable foundation for further scientific research and the development of new technical solutions in the field of big data processing

ACKNOWLEDGEMENTS

The research was supported by the grant of the National Research Foundation of Ukraine 2022.01/0135.

REFERENCES

[1] Baloch L., Bazai S., Marjan S., Aftab F., Aslam S., Neo K., and Amphawan A., "A Review of Big Data Trends and Challenges in Healthcare," International Journal of Technology, vol. 14, pp. 1320, (2023), doi: 10.14716/ijtech.v14i6.6643.

[2] Schmidhuber J., "Deep Learning in Neural Networks: An Overview," Neural Networks, vol. 61, pp. 85-117, (Jan. 2015), doi: 10.1016/j.neunet.2014.09.003.

[3] Le Cun Y., Bengio Y., and Hinton G., "Deep Learning," Nature, vol. 521, pp. 436-444, (May 2015), doi: 10.1038/nature14539.

[4] Poplavskyi O. A., Bondar O. A., Pavlov S. V., and Poplavska A. A., "Intelligent decision support systems for spot and futures exchange markets," Applied Geometry and Engineering Graphics, vol. 97, pp. 119-128, (2020). DOI: 10.32347/0131-579x.2020.97.119-128.

[5] Poplavska A., Vassilenko V., Poplavskyi O., and Casal D., "AI-Based Classification Algorithm of Infrared Images of Patients with Spinal Disorders", in IFIP Advances in Information and Communication Technology, vol. 626, pp. 316-323, (2021). DOI: 10.1007/978-3-030-78288-7_30.
[6] Vassilenko V., Poplavska A., Pavlov S., Kolisnyk P., Poplavskyi O., Kolisnyk S.,. Vitrova Y, and Wójcik W., "Automated features analysis of patients with spinal diseases using medical thermal images", in Proceedings of SPIE - The International Society for Optical Engineering, vol. 11456, Art. no. 114560L, (2020).
[7] Yao JKwok., J., and Geshengorn F., "Early stopping for non-parametric regression: Validation via softly-adaptive Rademacher complexities," Neurocomputing, vol. 194, pp. 139-147, (May 2016), doi: 10.1016/j.neucom.2016.02.020.
[8] Kvyetnyy R.N., Romanyuk O.N. et al. "Usage of the hybrid encryption in a cloud instant messages exchange system", Proc. SPIE 10031, Photonics Applications in Astronomy, Communications, Industry, and High-Energy Physics Experiments 2016, 100314S (28 September 2016); https://doi.org/10.1117/12.2249190
[9] Barmak, O.V., Mazurets, O.V., et al., "Information technology for creation of semantic structure of educational materials," Proc. SPIE 11176, 1117623 (2019). https://doi.org/10.1117/12.2537064
[10] Serkova V.K., Pavlov S.V., Romanava Va. A., et al. "Medical expert system for assessment of coronary heart disease destabilization based on the analysis of the level of soluble vascular adhesion molecules", Proc. SPIE 10445, Photonics Applications in Astronomy, Communications, Industry, and High Energy Physics Experiments 2017, 104453O (7 August 2017); https://doi.org/10.1117/12.2280984
[11] Avrunin O.G, Tymkovych M.Yu., et al. "Classification of CT-brain slices based on local histograms", Proc. SPIE 9816, Optical Fibers and Their Applications 2015, 98161J (17 December 2015); https://doi.org/10.1117/12.2229040
[12] Dzierżak, R., Omiotek, Z., Tkacz, E. and Kępa, A., "The Influence of the Normalisation of Spinal CT Images on the Significance of Textural Features in the Identification of Defects in the Spongy Tissue Structure," Innovations in Biomedical Engineering, 55-66 (2019).
[13] Andrushchenko, M., Selivanova, K., et al. "Hand movement disorders tracking by smartphone based on computer vision methods". Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 14(2), 5-10 (2024).
[14] Caviglione, L. and Coccoli, M., "Smart e-Learning Systems with Big Data," International Journal of Electronics and Telecommunications 64(4), 445–450 (2018). https://doi.org/10.24425/123544.
[15] Pavlov, S.V., Kozhukhar, A.T., Titkov, S.V., etc. "Electro-optical system for the automated selection of dental implants according to their colour matching", Przeglad Elektrotechniczny, , 93(3), 121–124, (2017).