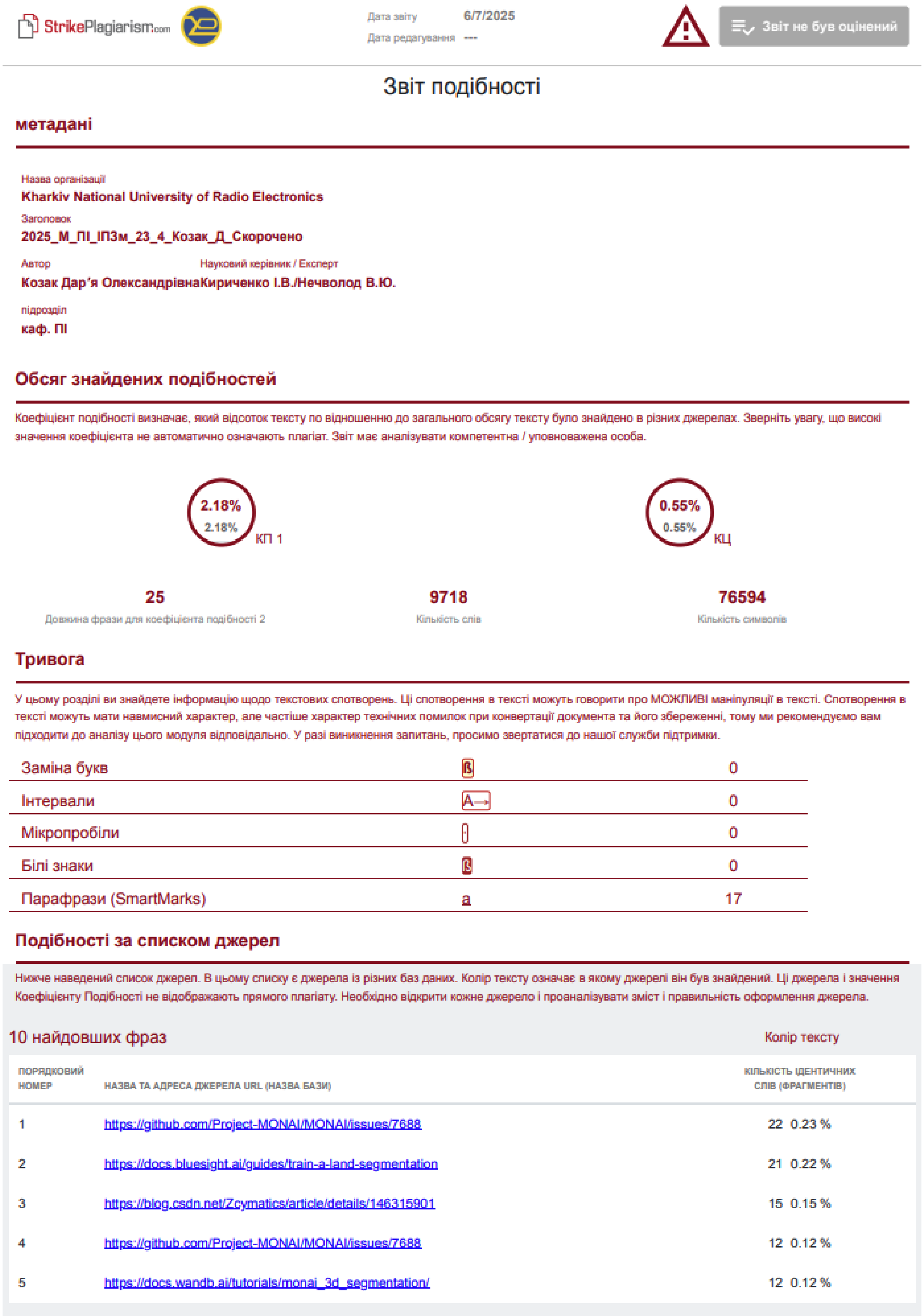
ДОДАТОК А

ЗВІТ РЕЗУЛЬТАТІВ ПЕРЕВІРКИ НА УНІКАЛЬНІСТЬ ТЕКСТУ В БАЗІ ХНУРЕ



Дата звіту 6/7/2025
Дата редагування ---

Звіт подібності

метадані

Назва організації
Kharkiv National University of Radio Electronics

Заголовок
2025_М_ПІ_ІПЗм_23_4_Козак_Д_Скорочено

Автор / Науковий керівник / Експерт
Козак Дар'я ОлександрівнаКириченко І.В./Нечволод В.Ю.

підрозділ
каф. ПІ

Обсяг знайдених подібностей

Коефіцієнт подібності визначає, який відсоток тексту по відношенню до загального обсягу тексту було знайдено в різних джерелах. Зверніть увагу, що високі значення коефіцієнта не автоматично означають плагіат. Звіт має аналізувати компетентна / уповноважена особа.

2.18%	0.55%
2.18%	0.55%
КП 1	КЦ

25	9718	76594
Довжина фрази для коефіцієнта подібності 2	Кількість слів	Кількість символів

Тривога

У цьому розділі ви знайдете інформацію щодо текстових спотворень. Ці спотворення в тексті можуть говорити про МОЖЛИВІ маніпуляції в тексті. Спотворення в тексті можуть мати навмисний характер, але частіше характер технічних помилок при конвертації документа та його збереженні, тому ми рекомендуємо вам підходити до аналізу цього модуля відповідально. У разі виникнення запитань, просимо звертатися до нашої служби підтримки.

Заміна букв	ß	0
Інтервали	A→	0
Мікропробіли	▯	0
Білі знаки	ß	0
Парафрази (SmartMarks)	a	17

Подібності за списком джерел

Нижче наведений список джерел. В цьому списку є джерела із різних баз даних. Колір тексту означає в якому джерелі він був знайдений. Ці джерела і значення Коефіцієнту Подібності не відображають прямого плагіату. Необхідно відкрити кожне джерело і проаналізувати зміст і правильність оформлення джерела.

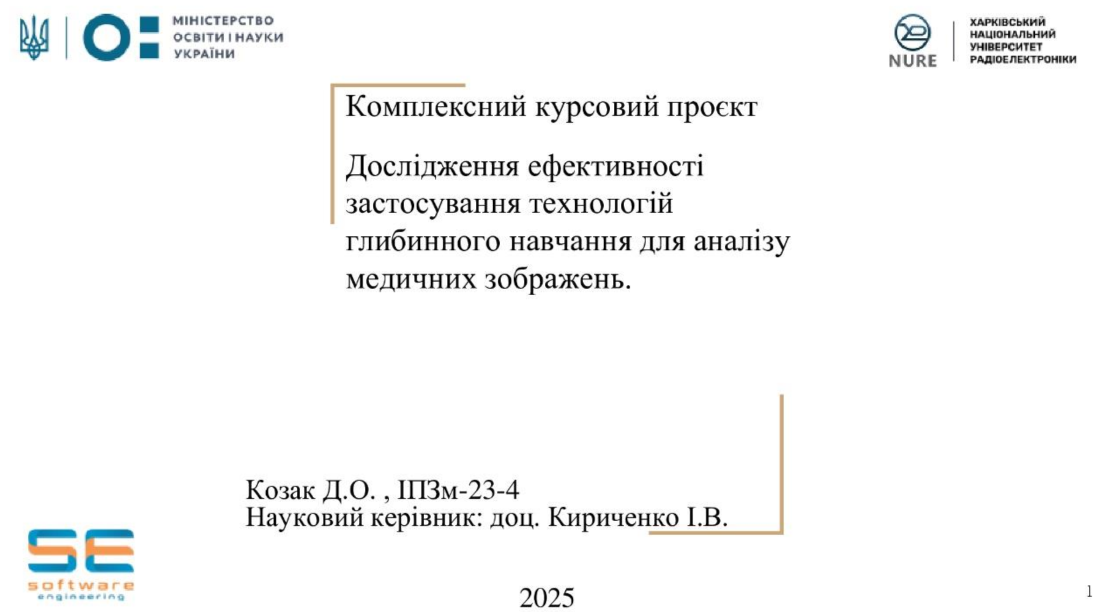
10 найдовших фраз — Колір тексту

ПОРЯДКОВИЙ НОМЕР	НАЗВА ТА АДРЕСА ДЖЕРЕЛА URL (НАЗВА БАЗИ)	КІЛЬКІСТЬ ІДЕНТИЧНИХ СЛІВ (ФРАГМЕНТІВ)
1	https://github.com/Project-MONAI/MONAI/issues/7688	22 0.23 %
2	https://docs.bluesight.ai/guides/train-a-land-segmentation	21 0.22 %
3	https://blog.csdn.net/Zcymatics/article/details/146315901	15 0.15 %
4	https://github.com/Project-MONAI/MONAI/issues/7688	12 0.12 %
5	https://docs.wandb.ai/tutorials/monai_3d_segmentation/	12 0.12 %

Рисунок А.1 – Звіт результатів перевірки на унікальність тексту в базі ХНУРЕ

ДОДАТОК Б

СЛАЙДИ ПРЕЗЕНТАЦІЇ



МІНІСТЕРСТВО ОСВІТИ І НАУКИ УКРАЇНИ

NURE ХАРКІВСЬКИЙ НАЦІОНАЛЬНИЙ УНІВЕРСИТЕТ РАДІОЕЛЕКТРОНІКИ

Комплексний курсовий проєкт

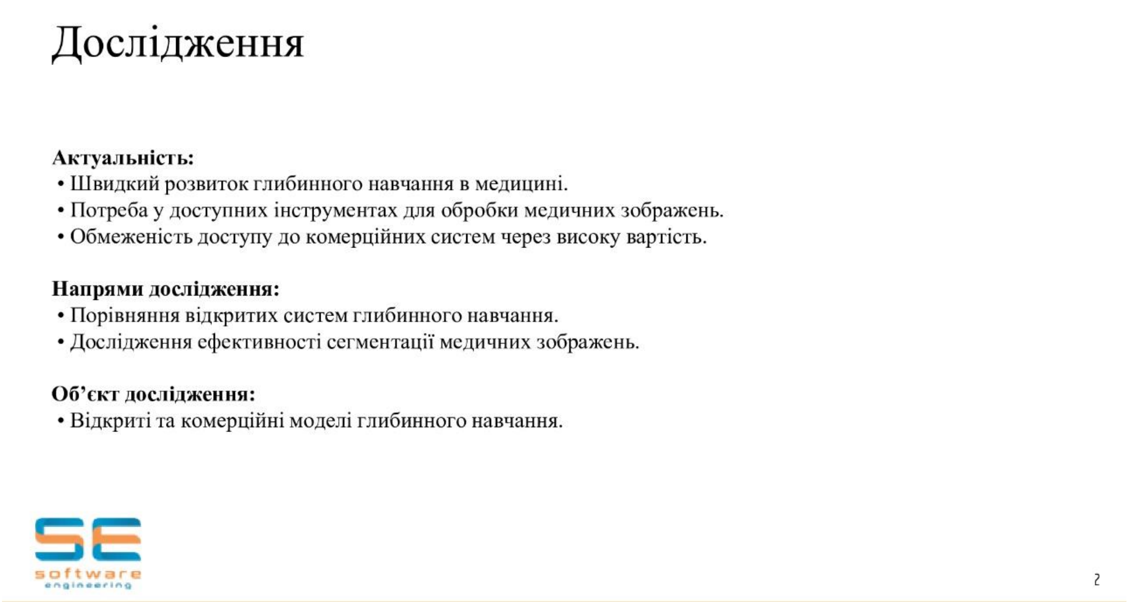
Дослідження ефективності застосування технологій глибинного навчання для аналізу медичних зображень.

Козак Д.О. , ІПЗм-23-4
Науковий керівник: доц. Кириченко І.В.

SE software engineering

2025

Рисунок Б.1 – Слайд 1 презентації



Дослідження

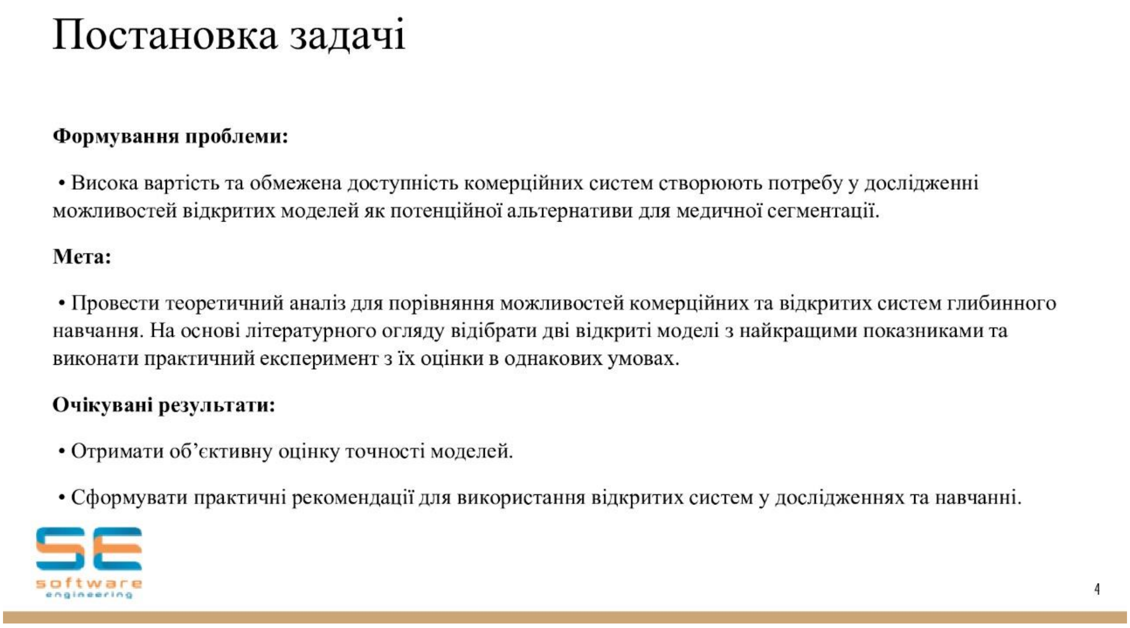
Актуальність:
- Швидкий розвиток глибинного навчання в медицині.
- Потреба у доступних інструментах для обробки медичних зображень.
- Обмеженість доступу до комерційних систем через високу вартість.

Напрями дослідження:
- Порівняння відкритих систем глибинного навчання.
- Дослідження ефективності сегментації медичних зображень.

Об’єкт дослідження:
- Відкриті та комерційні моделі глибинного навчання.

SE software engineering

Рисунок Б.2 – Слайд 2 презентації



Постановка задачі

Формування проблеми:

• Висока вартість та обмежена доступність комерційних систем створюють потребу у дослідженні можливостей відкритих моделей як потенційної альтернативи для медичної сегментації.

Мета:

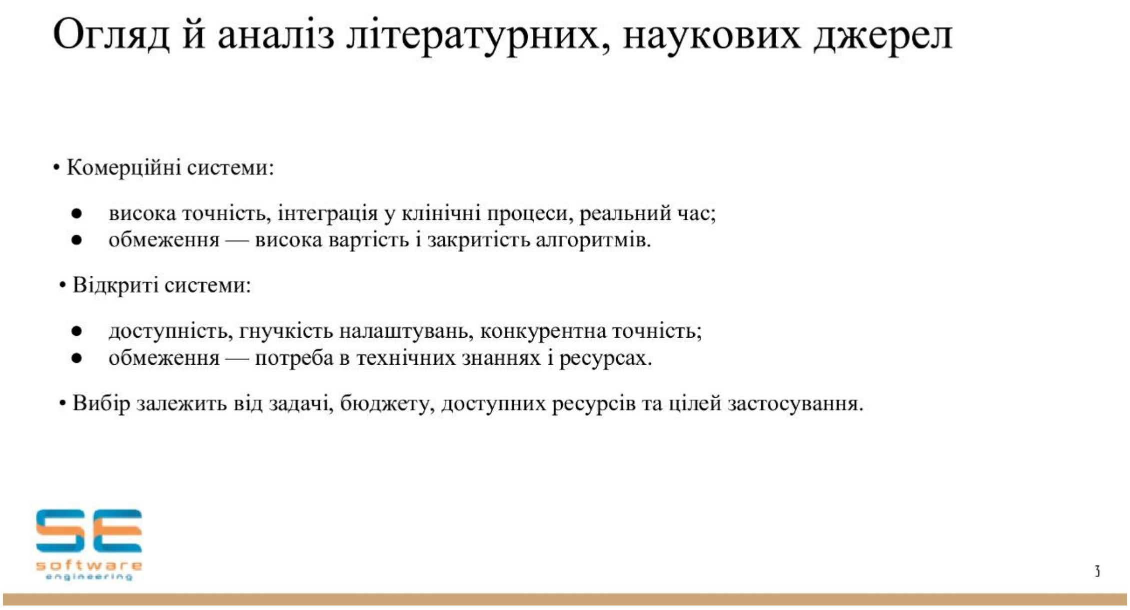
• Провести теоретичний аналіз для порівняння можливостей комерційних та відкритих систем глибинного навчання. На основі літературного огляду відібрати дві відкриті моделі з найкращими показниками та виконати практичний експеримент з їх оцінки в однакових умовах.

Очікувані результати:

• Отримати об’єктивну оцінку точності моделей.

• Сформувати практичні рекомендації для використання відкритих систем у дослідженнях та навчанні.

Рисунок Б.3 – Слайд 3 презентації



Огляд й аналіз літературних, наукових джерел

• Комерційні системи:

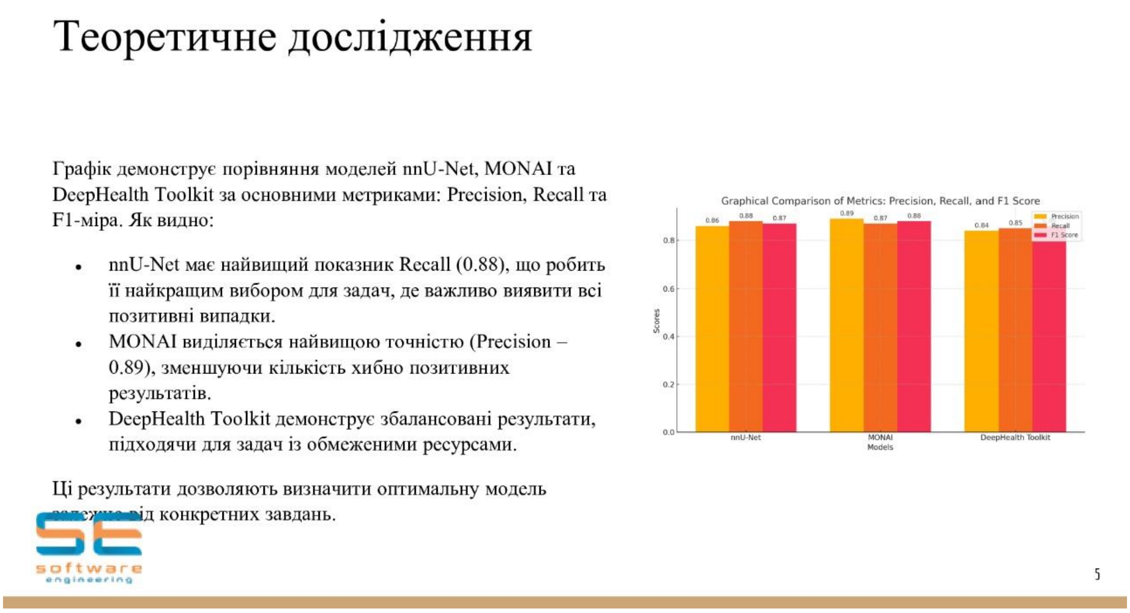
- висока точність, інтеграція у клінічні процеси, реальний час;
- обмеження — висока вартість і закритість алгоритмів.

• Відкриті системи:

- доступність, гнучкість налаштувань, конкурентна точність;
- обмеження — потреба в технічних знаннях і ресурсах.

• Вибір залежить від задачі, бюджету, доступних ресурсів та цілей застосування.

Рисунок Б.4 – Слайд 4 презентації



Теоретичне дослідження

Графік демонструє порівняння моделей nnU-Net, MONAI та DeepHealth Toolkit за основними метриками: Precision, Recall та F1-міра. Як видно:

- nnU-Net має найвищий показник Recall (0.88), що робить її найкращим вибором для задач, де важливо виявити всі позитивні випадки.
- MONAI виділяється найвищою точністю (Precision – 0.89), зменшуючи кількість хибно позитивних результатів.
- DeepHealth Toolkit демонструє збалансовані результати, підходячи для задач із обмеженими ресурсами.

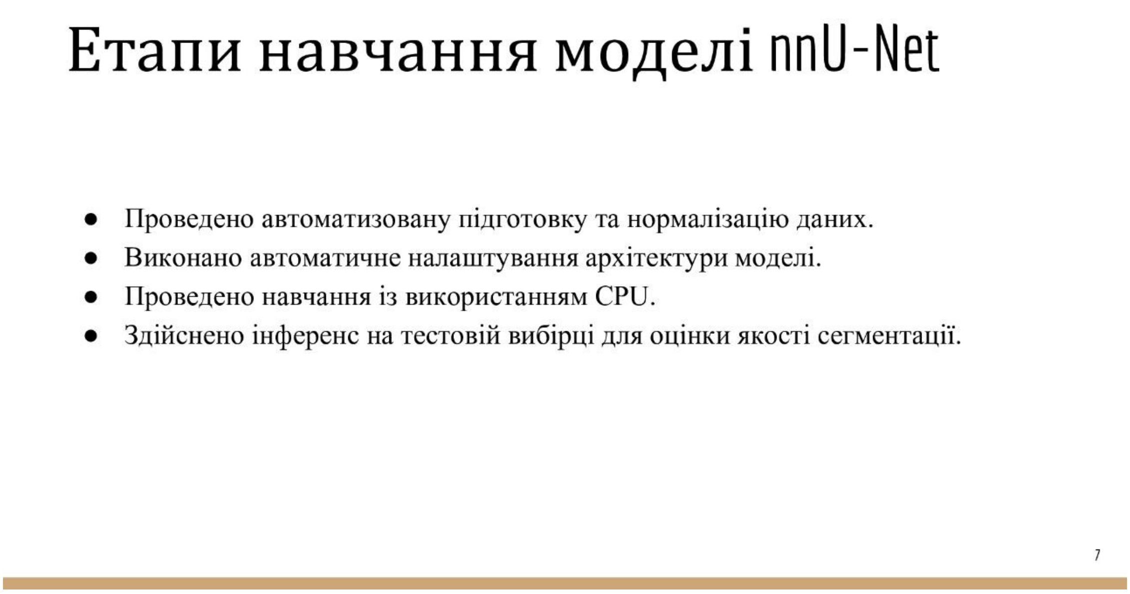
Ці результати дозволяють визначити оптимальну модель залежно від конкретних завдань.

Рисунок Б.5 – Слайд 5 презентації

Методології виконання практичного експерименту

- ★ **Викорисиані методи:**
  - ○ Вибрано датасет MSD Task03_Liver.
  - ○ Навчання моделей проводилось локально (CPU).
  - ○ Порівняння моделей у рівних умовах.
  - ○ Використання однакових метрик оцінки: Dice, Precision, Recall, F1.
- ★ **Інструменти та технології:**
  - ○ nnU-Net v2
  - ○ MONAI (на базі PyTorch)
  - ○ Мова програмування Python
  - ○ Набір даних MSD Task03_Liver
  - ○ Середовище: MacBook Pro (M3 Pro, CPU)

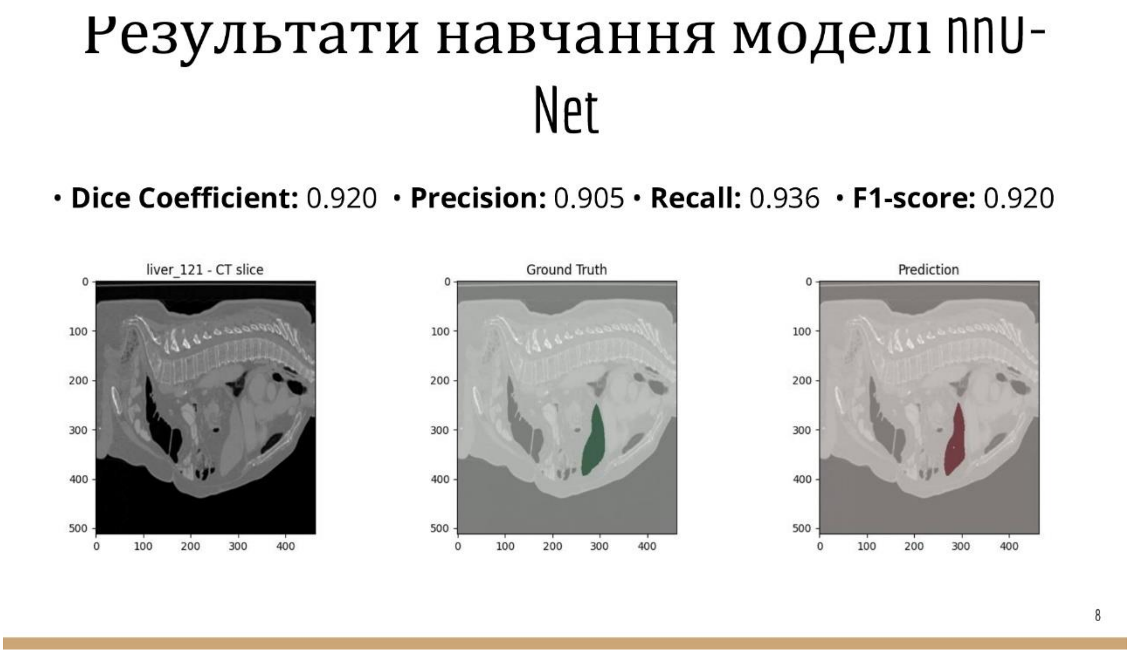
Рисунок Б.6 – Слайд 6 презентації



Етапи навчання моделі nnU-Net

- Проведено автоматизовану підготовку та нормалізацію даних.
- Виконано автоматичне налаштування архітектури моделі.
- Проведено навчання із використанням CPU.
- Здійснено інференс на тестовій вибірці для оцінки якості сегментації.

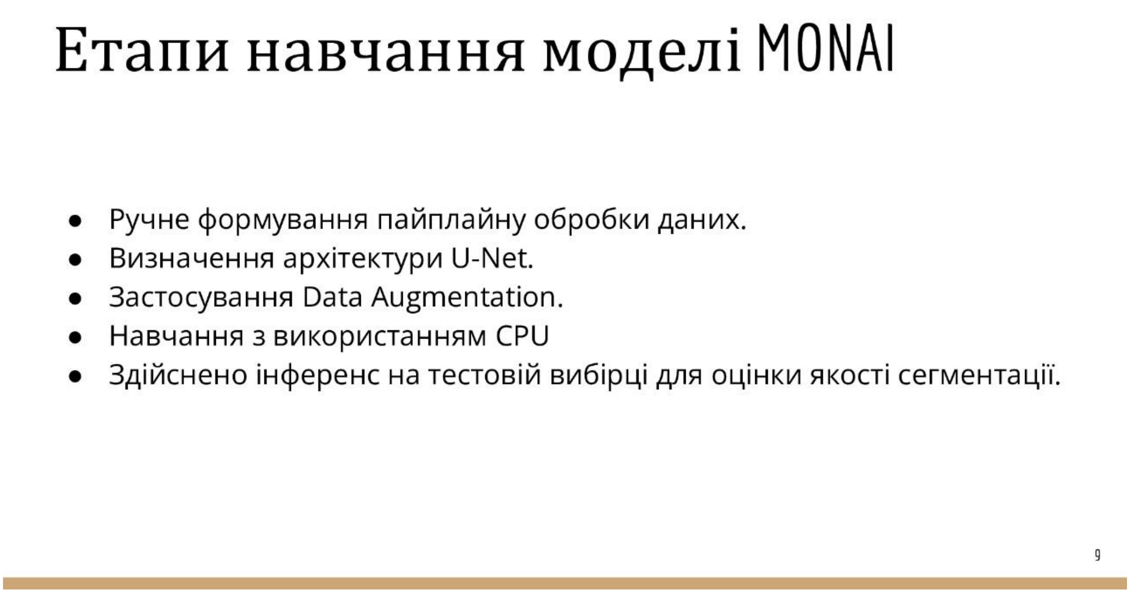
Рисунок Б.7 – Слайд 7 презентації



Результати навчання моделі nnU-Net

• **Dice Coefficient:** 0.920 • **Precision:** 0.905 • **Recall:** 0.936 • **F1-score:** 0.920

Рисунок Б.8 – Слайд 8 презентації



Етапи навчання моделі MONAI

- Ручне формування пайплайну обробки даних.
- Визначення архітектури U-Net.
- Застосування Data Augmentation.
- Навчання з використанням CPU
- Здійснено інференс на тестовій вибірці для оцінки якості сегментації.

Рисунок Б.9 – Слайд 9 презентації

Результати навчання моделі MONAI

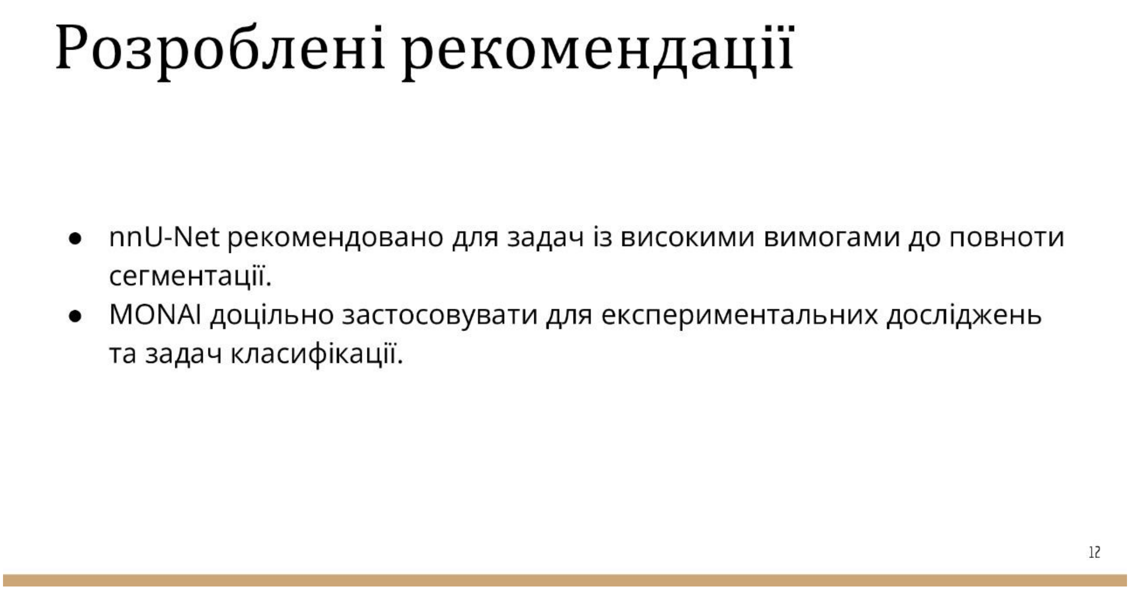
• **Dice Coefficient:** 0.882 • **Precision:** 0.461 • **Recall:** 1.000 • **F1-score:** 0.882

Рисунок Б.10 – Слайд 10 презентації

Порівняльний аналіз результатів

- nnU-Net перевищив MONAI за точністю та збалансованістю.
- MONAI демонструє високу чутливість, але нижчу специфічність.
- Обидві моделі підтвердили свою придатність для задач медичної сегментації.

Рисунок Б.11 – Слайд 11 презентації

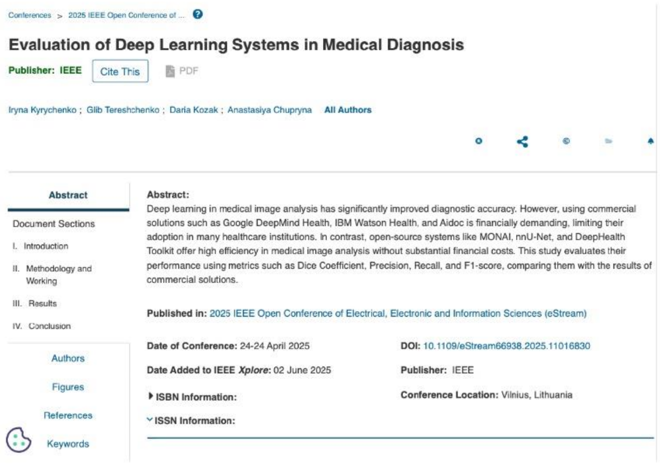


Розроблені рекомендації

- nnU-Net рекомендовано для задач із високими вимогами до повноти сегментації.
- MONAI доцільно застосовувати для експериментальних досліджень та задач класифікації.

Рисунок Б.12 – Слайд 12 презентації

Публікація



Conferences > 2025 IEEE Open Conference of ...

Evaluation of Deep Learning Systems in Medical Diagnosis

Publisher: IEEE

Iryna Kyrychenko ; Glib Tereshchenko ; Daria Kozak ; Anastasiya Chupryna **All Authors**

Abstract:
Deep learning in medical image analysis has significantly improved diagnostic accuracy. However, using commercial solutions such as Google DeepMind Health, IBM Watson Health, and Aidoc is financially demanding, limiting their adoption in many healthcare institutions. In contrast, open-source systems like MONAI, nnU-Net, and DeepHealth Toolkit offer high efficiency in medical image analysis without substantial financial costs. This study evaluates their performance using metrics such as Dice Coefficient, Precision, Recall, and F1-score, comparing them with the results of commercial solutions.

Published in: 2025 IEEE Open Conference of Electrical, Electronic and Information Sciences (eStream)

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ISBN Information:

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DOI: 10.1109/eStream66938.2025.11016830

Publisher: IEEE

Conference Location: Vilnius, Lithuania

Рисунок Б.13 – Слайд 13 презентації

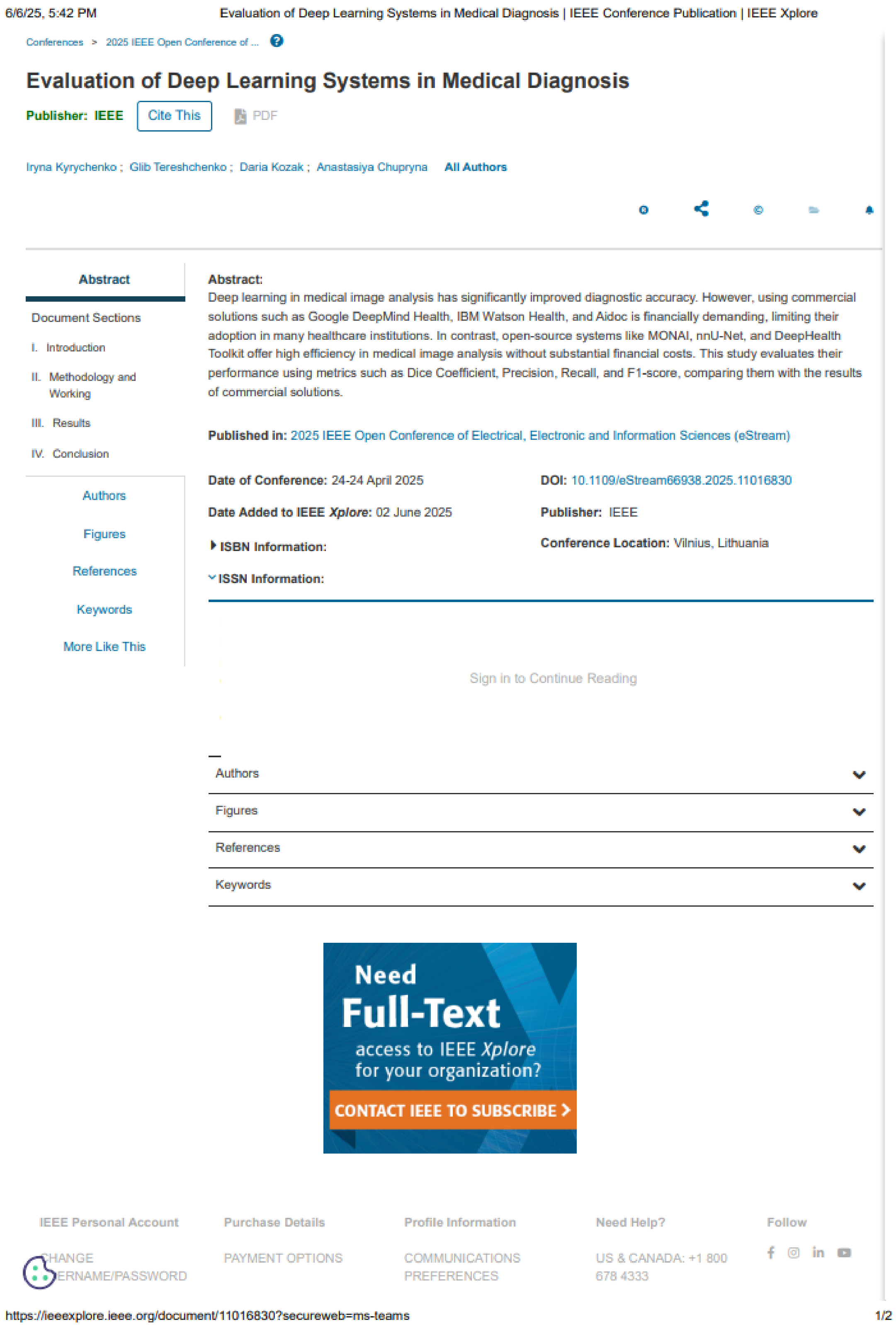
Висновки

- Відкриті системи глибинного навчання демонструють високу ефективність.
- nnU-Net забезпечує автоматизацію та стабільність.
- MONAI пропонує гнучкість та розширюваність.
- Отримані результати можуть бути основою для подальших досліджень та впровадження у практику.

Рисунок Б.14 – Слайд 14 презентації

ДОДАТОК В

АПРОБАЦІЯ РЕЗУЛЬТАТІВ РОБОТИ. СТАТТЯ



6/6/25, 5:42 PM Evaluation of Deep Learning Systems in Medical Diagnosis | IEEE Conference Publication | IEEE Xplore

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Рисунок В.1 – Голона сторінка статті

Evaluation of Deep Learning Systems in Medical Diagnosis

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The application of deep learning in medical image analysis has significantly improved diagnostic accuracy. However, the use of commercial solutions such as Google DeepMind Health, IBM Watson Health, and Aidoc is financially demanding, limiting their adoption in many healthcare institutions. In contrast, open-source systems like MONAI, nnU-Net, and DeepHealth Toolkit offer high efficiency in medical image analysis without substantial financial costs. This study evaluates their performance using metrics such as Dice Coefficient, Precision, Recall, and F1-score, comparing them with the results of commercial solutions.

Keywords – deep learning, medical imaging, neural networks, artificial intelligence, nnU-Net, MONAI, DeepHealth Toolkit, performance evaluation i

I. INTRODUCTION

Medical image analysis is a critically important task in modern medicine, as it enables early disease diagnosis, monitoring of disease progression, and evaluation of treatment effectiveness. Due to technological advancements and the development of deep learning methods, medical imaging has undergone significant changes over the past decade. Artificial intelligence (AI) methods allow for the automation of complex analysis processes, reducing the likelihood of human error, increasing data processing speed, and ensuring more accurate results.

Deep learning is one of the most promising areas in medical diagnostics. Convolutional neural networks (CNNs) can automatically extract key features from images without the need for manual filter adjustments. This capability opens new possibilities for organ segmentation, pathology detection, and the assessment of tissue changes. However, the widespread adoption of commercial solutions such as Google DeepMind Health, IBM Watson Health, and Aidoc requires substantial financial resources, limiting their use, especially in middle-income countries [1-3].

As an alternative, open-source deep learning systems, such as MONAI, nnU-Net, and DeepHealth Toolkit, provide researchers and developers with flexible and accessible tools for creating and improving medical image analysis algorithms. These systems allow for the testing and implementation of advanced analysis methods, opening new opportunities for research and the practical integration of AI technologies in medical practice [4-6].

The objective of this study is to evaluate the effectiveness of open-source deep learning systems for medical image analysis and to assess their potential as alternatives to commercial solutions in scientific and clinical research. The key tasks include:

- Analysing existing open-source deep learning systems for medical image analysis and their architectures.
- Evaluating the performance of open models using quantitative metrics such as Dice Coefficient, Precision, Recall, and F1-score.
- Comparing the results of open-source solutions with publicly available data from commercial platforms.
- Identifying the strengths and weaknesses of open systems in the context of practical applications.

Thus, this study aims to investigate the efficiency of open-source deep learning systems, which holds not only scientific significance but also practical value for the advancement of medical technologies.

II. METHODOLOGY AND WORKING

Segmentation and Classification in Medical Analysis

Segmentation and classification are two key tasks in the analysis of medical images using deep learning.

Segmentation is the process of dividing an image into separate regions, each corresponding to a specific object or structure. In a medical context, this may involve delineating the boundaries of tumours, organs, or pathological structures. Modern segmentation methods, such as U-Net and nnU-Net, provide high accuracy due to specialized architectures that utilize an encoder-decoder structure and skip connections to preserve spatial information. According to research, applying deep learning for spatial interpretation of medical images significantly improves the accuracy of pathology segmentation in X-ray images [7].

Classification is the process of assigning an image or its part to a specific class, such as identifying the type of lesion or the stage of a disease. Deep neural networks, such as ResNet and EfficientNet, effectively handle these tasks by analysing image features and detecting patterns associated with specific pathologies. Studies have shown that the use of convolutional neural networks for medical image processing increases classification accuracy by 15-20% compared to traditional analysis methods [8].

Research on Convolutional Neural Networks in Medical Analysis

Convolutional neural networks (CNNs) form the backbone of most modern medical image analysis systems. They are used for automatic pathology identification, organ segmentation, and tissue condition assessment. Due to their multi-layered structure, CNNs can detect complex patterns in medical images, making them an ideal tool for applications in radiology and oncology.

DeepHealth Toolkit utilizes convolutional networks for the segmentation and analysis of 3D medical images. Its key feature is the hybrid approach, which combines classical image analysis methods with modern neural network algorithms. This system efficiently processes multi-layered X-ray and tomographic data, making it highly useful in radiology.

U-Net is one of the most popular convolutional neural networks (CNN) architectures, specifically designed for segmentation tasks, particularly in medical imaging. It features a symmetric structure, consisting of an encoder and a decoder.

- The encoder performs convolutional operations to extract features while gradually reducing the dimensionality of input data.
- The decoder restores spatial information and generates the segmentation mask.

A key feature of U-Net is the presence of skip connections between corresponding levels of the encoder and decoder. These connections help preserve high-resolution details that would otherwise be lost during convolutions, thereby improving the model's accuracy (Fig. 1).

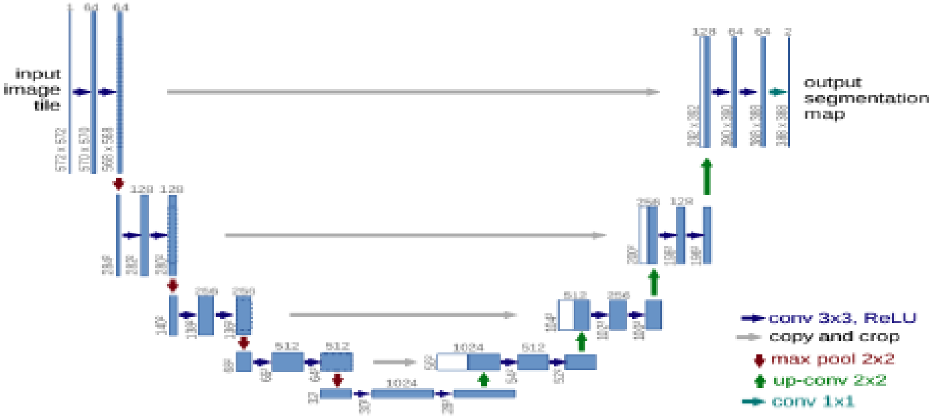

Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations [9].

U-Net has gained widespread recognition due to its ability to work effectively with small datasets, which is a common challenge in medical applications. Studies indicate that U-Net can be adapted for various tasks, including 2D and 3D image segmentation, making it a versatile tool in medical analysis [9].

nnU-Net is an advanced version of U-Net that automatically adapts to any medical imaging dataset, optimizing hyperparameters without manual adjustments.

The nnU-Net workflow starts with data preprocessing, where images are normalized, rescaled, and cropped if necessary to fit standard dimensions. These preprocessing steps are critical, as the quality of input data directly impacts model performance.

After preprocessing, the model automatically adapts its architecture to the specific dataset, selecting the optimal input image size, network depth, the number of channels in convolutional layers, and other parameters. This automation reduces the time and computational resources typically required for manual tuning.

The nnU-Net architecture follows a three-stage process:

- Downsampling – the model extracts global image features through a series of convolutional and maxpooling layers, reducing dimensionality for efficient processing.

- Bottleneck – snformation is compressed into the most compact representation, allowing for effective feature extraction.
- Upsampling – the image is reconstructed to its original resolution, integrating both local and global features.

Despite its versatility, nnU-Net has some limitations. The automated configuration does not always yield optimal results for highly complex or diverse datasets. For example, when working with data that contains a high degree of variability or artifacts, manual fine-tuning may still be necessary.

ResNet is one of the most widely used CNN architectures for classification and image analysis tasks. Its main innovation is the use of residual blocks, which incorporate direct connections between layers (Fig. 2). This design eliminates the vanishing gradient problem, which is common in deep networks, and significantly simplifies training.

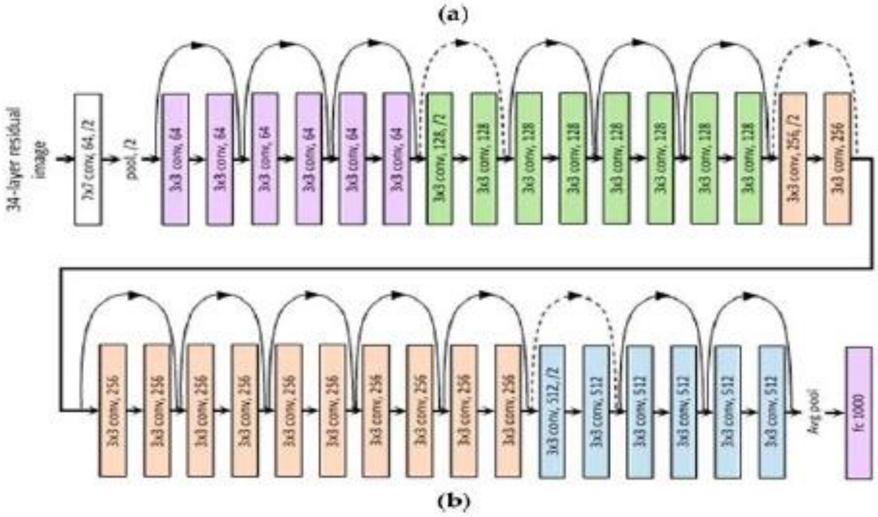

Fig.2. ResNet - 34 Layered architecture [10].

Moreover, ResNet can be effectively used for segmentation if complemented with a decoder module like U-Net.

ResNet scales well, allowing it to be utilized for large datasets and complex tasks. However, its performance is highly dependent on computational resources, making high-memory GPUs recommended for optimal operation. This limits its suitability for resource-constrained environments, but it remains an ideal choice for large-scale research projects.

MONAI (Medical Open Network for AI) is a modular deep learning platform designed for medical applications, allowing for flexible adaptation to specific tasks.

Data Preparation in MONAI involves extensive data augmentation techniques such as scaling, rotation, cropping, and normalization. These transformations enhance dataset diversity, improving the model's ability to generalize.

A key feature of MONAI is its integration of pre-trained models (such as ResNet and DenseNet), which have been trained on large datasets, reducing the need for prolonged training. MONAI has been shown to improve the efficiency of medical diagnostic models significantly. Research indicates that MONAI outperforms traditional approaches, achieving over 90% accuracy in tomography image analysis [11].

Evaluation of Effectiveness by Metrics

The Dice coefficient is widely used to assess segmentation quality. It determines the similarity between the predicted mask (P) and the ground truth annotation (G) and is calculated using Equation (1).

$$DICE = (2*|P\cap G|)/(|P|+|G|) \qquad (1)$$

In studies, the nnU-Net model demonstrated an average Dice coefficient of 0.89 in brain tumor segmentation tasks, confirming its ability to accurately define object boundaries. MONAI showed an average Dice coefficient of 0.91 for liver segmentation, indicating optimal model tuning for specific

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tasks. DeepHealth Toolkit achieved 0.87 in heart segmentation tasks [12-14].

Precision measures the proportion of correctly predicted positive samples (TP) among all predicted positive samples and is calculated using Equation (2).

$$Percision = TP/(TP+FP) \qquad (2)$$

This metric is important in tasks where it is critical to reduce the number of false positive results. In studies, nnU-Net showed a Precision of 0.86 in brain tumor segmentation tasks. MONAI achieved a Precision of 0.89 in skin cancer lesion classification, which indicates a high level of prediction in specialized scenarios. DeepHealth Toolkit reached a Precision of 0.84 in lung anomaly classification tasks [12-14].

Recall determines the proportion of true positive samples correctly predicted by the model. Its formula (3) is as follows:

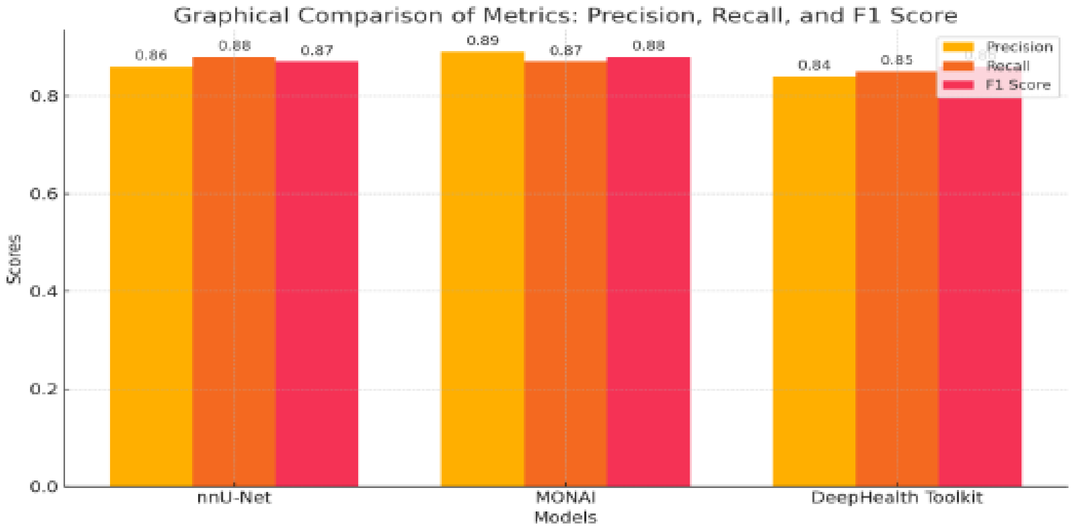
$$Recall= TP/(TP+FN) \qquad (3)$$

This metric is important for tasks where it is critical not to miss positive cases, such as detecting serious pathologies. In the study, nnU-Net achieved a high Recall (0.88), confirming its ability to identify most positive samples. For MONAI, Recall was 0.87 in liver segmentation tasks, while DeepHealth Toolkit showed 0.85 in lung anomaly classification tasks [12-14].

III. RESULTS

Comparison and evaluation of efficiency in classification problems

To compare the effectiveness of open models in classification tasks, a graph (Fig. 3) was built, visualizing key metrics – Precision, Recall, and F1-score – for nnU-Net, MONAI, and DeepHealth Toolkit. The analysis showed that MONAI demonstrates the best results in classification tasks due to its flexible tuning and adaptation to specialized datasets. nnU-Net provides stable performance across a wide range of medical tasks, especially in segmentation, while DeepHealth Toolkit is effective for analysing complex three-dimensional images, although its performance depends on the available computational resources (Fig. 3).



Fsg.3. Graphical comparison of Precision, Recall, and F1 Score metrics for nnU-Net, MONAI, and DeepHealth Toolkit models.

Comparison of Open-Source and Commercial Deep Learning Systems

A comparison and summary of the characteristics of open-source and commercial deep learning systems have been conducted, with the results presented in Table I, which highlights the main features of these platforms.

The Table 1 illustrates the key characteristics of each platform, their advantages, and limitations, providing a clear understanding of their suitability for specific tasks. Open-source systems, such as nnU-Net and MONAI, are suitable for a wide range of research tasks due to their flexibility and accessibility. In contrast, commercial solutions are distinguished by their integration with clinical systems, giving them a significant advantage in practical applications.

TABLE I. COMPARISON OF OPEN-SOURCE AND COMMERCIAL DEEP LEARNING SYSTEMS

Characteristic	*nnU-Net*	*MONAI*	*DeepHealth Toolkit*	*Google DeepMind Health*	*IBM Watson Health*	*Aidoc*
Primary Purpose	Segmentation of medical images	Segmentation, classification, regression	Segmentation, classification, hybrid tasks	Early diagnosis, pathology analysis	Oncology, mammogram analysis	Radiological analysis, expert assessment
Automation of Tuning	Full	Partial	Absent	Full	Partial	Full
Supported Data Formats	NIfTI, limited support for other formats	DICOM, NIfTI	DICOM, NIfTI, PNG	DICOM	DICOM, NIfTI	DICOM
Data Processing Algorithms	3D-UNet	Various models (3D-UNet, ResNet, DenseNet)	ResNet, InceptionNet, hybrid algorithms	Proprietary CNN-based models	Proprietary CNN models with NLP support	Modified CNN
Flexibility	Medium	High	High	Medium	Medium	Medium
Key Advantages	Versatility, automation	Hybrid approach, adaptability to different datasets	High accuracy, integration with external resources	High accuracy, integration with healthcare systems	Integration with clinical systems	Real-time analysis speed
Main Drawbacks	High GPU requirements, limited flexibility	Complexity of learning	High demand for knowledge and resources	High cost	High cost	High cost
Characteristic	nnU-Net	MONAI	DeepHealth Toolkit	Google DeepMind Health	IBM Watson Health	Aidoc
Primary Purpose	Segmentation of medical images	Segmentation, classification, regression	Segmentation, classification, hybrid tasks	Early diagnosis, pathology analysis	Oncology, mammogram analysis	Radiological analysis, expert assessment
Automation of Tuning	Full	Partial	Absent	Full	Partial	Full
Supported Data Formats	NIfTI, limited support for other formats	DICOM, NIfTI	DICOM, NIfTI, PNG	DICOM	DICOM, NIfTI	DICOM
Data Processing Algorithms	3D-UNet	Various models (3D-UNet, ResNet, DenseNet)	ResNet, InceptionNet, hybrid algorithms	Proprietary CNN-based models	Proprietary CNN models with NLP support	Modified CNN

IV. CONCLUSION

Open-source deep learning systems, such as nnU-Net, MONAI, and DeepHealth Toolkit, have demonstrated significant efficiency in medical image analysis tasks, offering a wide range of possibilities for researchers and developers. These platforms provide flexibility, accessibility, and competitiveness compared to commercial solutions, as they enable working with diverse datasets and customizing models to meet specific user needs. Thanks to their open-source nature and adaptability to specialized tasks, these systems are actively used in scientific research and clinical practice.

Among open-source solutions, nnU-Net is one of the most efficient approaches for medical image segmentation. Its main advantage lies in fully automated parameter tuning, allowing high-performance results without the need for manual optimization. In numerous studies, this model has consistently demonstrated high accuracy in organ segmentation, tumor detection, and anomaly identification, making it an ideal choice for analysing X-ray, CT, and MRI scans.

MONAI, in turn, is one of the most versatile open-source platforms for medical image analysis. It supports a wide range of neural network architectures, including ResNet, U-Net, and their modifications, enabling its application in various medical tasks. MONAI delivers optimal results in classification tasks and specialized scenarios such as anomaly detection in tomographic images. Furthermore, its adaptability to different data formats and seamless integration with PyTorch make it a convenient tool for research projects and practical medical applications.

DeepHealth Toolkit is a valuable tool for analyzing complex 3D structures, such as cardiovascular systems or intracranial objects. Its key advantage is the hybrid approach, which combines classical image analysis algorithms with modern neural network methods. However, the effectiveness of this system heavily depends on available computational resources, which may limit its widespread adoption in clinical practice.

On the other hand, commercial platforms, such as Google DeepMind Health, IBM Watson Health, and Aidoc, offer seamless integration with clinical systems and provide high-precision image analysis in real-world medical environments. With numerous pre-trained models and powerful cloud computing capabilities, these solutions are optimized for deployment in large medical canters and hospitals. However, the high cost of these products significantly restricts their accessibility for institutions with limited budgets, making their use challenging in underfunded healthcare facilities and research projects.

Thus, open-source deep learning systems are powerful tools for the scientific community, as they enable achieving high performance at relatively low costs. They offer flexibility and adaptability, making them ideal for various research tasks and even some clinical applications. At the same time, commercial platforms remain essential for large-scale implementation in complex clinical environments, where accuracy and processing speed play a crucial role.

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ДОДАТОК Г

ЕКСПЕРНИЙ ВИСНОВОК РЕЗУЛЬТАТІВ ПЕРЕВІРКИ КВАЛІФІКАЦІЙНОЇ РОБОТИ НА ВІДПОВІДНІСТЬ ОФОРМЛЕННЯ ВИМОГАМ ДСТУ 3008:2015

Експертний висновок результатів перевірки кваліфікаційної роботи

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Дар'я КОЗАК
(прізвище, ім'я, по батькові)

Зауваження

Пункт ДСТУ 3008-2015	Зміст пункту	Сторінка кваліфікаційної роботи
1	2	3
	7.1 Загальні положення	
	7.3 Нумерація сторінок звіту	
	7.5 Рисунки	
	7.6 Таблиці	
	7.7 Переліки	
	7.8 Примітки	
	7.9 Виноски	
	7.10 Формули та рівняння	
	7.11 Посилання	
	7.13 Список авторів	
	7.14 Скорочення та умовні познаки	
	7.15 Додатки	

Експерт ______ (підпис) Вадим НЕЧВОЛОД (прізвище, ініціали)

Зауважень з оформлення немає
07.06.2025

Рисунок Г.1 – Експертний висновок результатів перевірки кваліфікаційної роботи на відповідність оформлення вимогам ДСТУ 3008: 2015