



METHODS OF APPLICATION OF COMPUTER VISION IN MEDICINE

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Abstract

This article briefly discusses the ancient traditions, values, and the rich cultural heritage of the Uzbek people, which has a long and significant history.

Keywords: literature and art, craftsmanship, architecture, historical sources, national clothing, traditions, monuments.

Introduction

In modern medicine, the development of information technologies, in particular artificial intelligence, is taking diagnostic, treatment and monitoring processes to a new level. Computer vision — a technology that allows for the automatic study and interpretation of visual data — is gaining importance, especially in working with medical images.

This technology is used not only in diagnosis, but also in planning operations, detecting abnormalities, and detecting diseases at an early stage.

Methodology

This study uses a mixed-methods approach, including literature review, interviews with healthcare IT experts in Uzbekistan, and case analysis of pilot initiatives in telemedicine and diagnostic imaging. Data sources include official reports from the Ministry of Health, World Bank e-health programs in Uzbekistan, and regional case studies. Comparative benchmarks with neighboring Central Asian countries were also used to contextualize Uzbekistan’s progress.

Literature Review and Analyse

Computer vision is a field of artificial intelligence that analyzes visual information, automatically segmenting, classifying, and interpreting images. Traditionally, CV

has been applied to three main types of problems: classification, detection, and segmentation.



Figure 1. Types of CV applications.

Solutions to these problems are similar to using a single photo of a cat as an example.

Classification

These are the simplest tasks - to understand whether an image belongs to a certain class or not. The result is always binary: if the image belongs to this class, then "yes" (1), if not, then "no" (0). There is also "multiple classification", in which one image can belong to several classes.

Classification in its pure form in medicine is not very common. For example, for the task of determining whether there are suspicious areas in an X-ray image, a "yes" or "no" answer is not enough, and it needs to be clarified. The following tasks solve them: detection and segmentation.

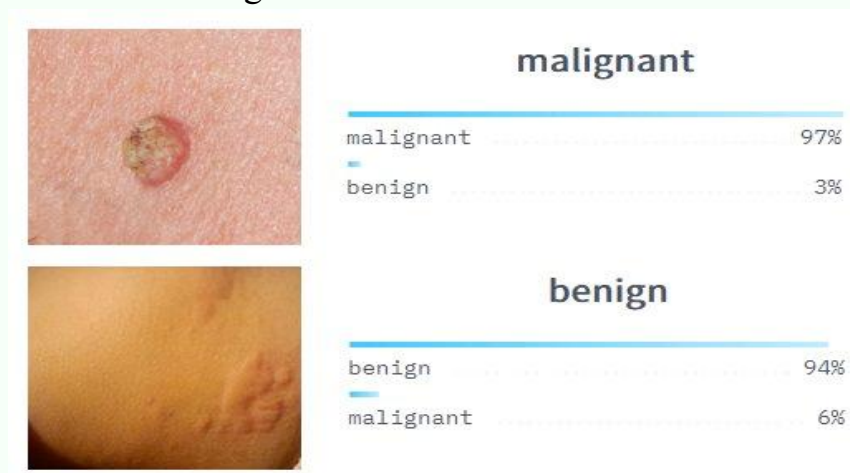


Figure 2. A photo of a skin lesion in a model.

In this example, the model takes a photo of a skin lesion as input and classifies it as benign or malignant.

Detection

In solving this problem, the model not only responds to the presence of an object in the image, but also detects it - determines its approximate boundaries.

If the image is two-dimensional, the model finds four corner points that form a rectangle around the object. For three-dimensional images, a parallelepiped is constructed instead of a rectangle, so eight points are needed. When working with video, detection can be transformed into a tracking task: the model must not only detect the object, but also track its movement in the frame.

Continuing with the X-ray example, the detection task is to determine exactly where the suspicious area is. The detected area can then be sent to a classifier to answer the question of whether it is a tumor or not.



Figure 3. Detection task.

During the Covid restrictions, the detection task was used in conjunction with classification to determine whether a person is wearing a mask. The detector identifies a face in the image, and the classifier checks whether it belongs to the “masked face” class. [8]

Segmentation

This is a more complex task - the model classifies each pixel and defines the exact boundaries of the object. There are two types of segmentation:

- semantic - identifies different classes of objects. For example, in an image with several cysts, the model recognizes them all and assigns them to the general class “cyst”;
- instance - highlights specific objects. In the same image, the model gives each brush its own number or symbol.

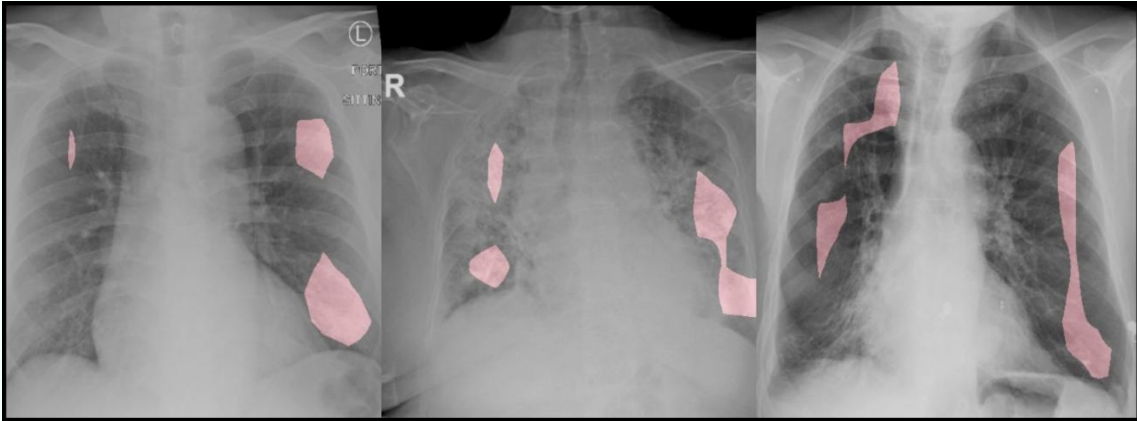


Figure 4. Model segments.

Here, the model performs semantic segmentation—it highlights dark areas in the patient’s lungs in red. The doctor then evaluates them and draws a conclusion. [9]

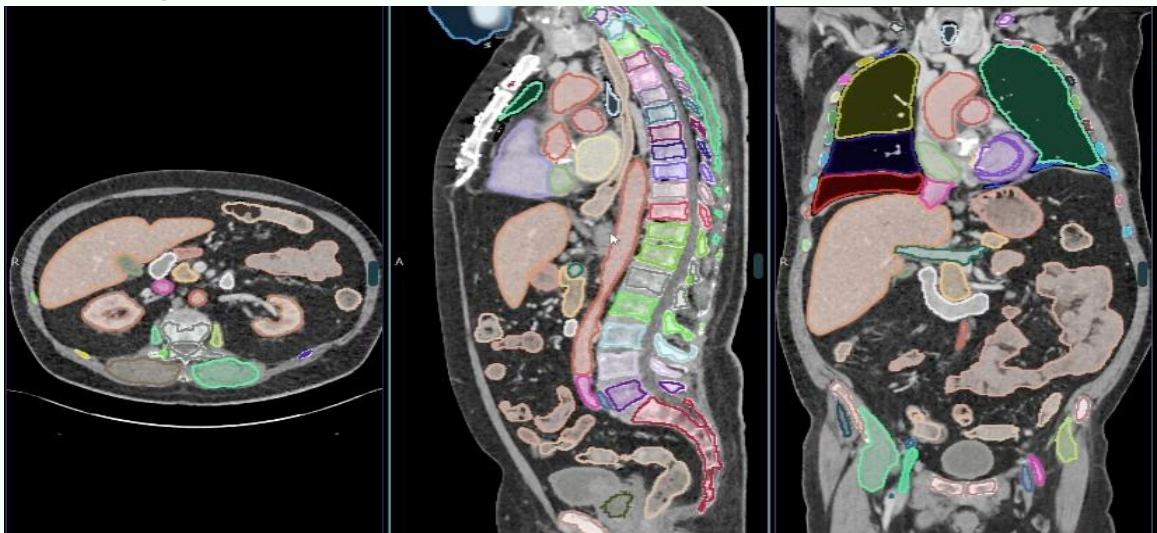


Figure 5. The image is taken as a separate object.

An example of segmentation. In the image, each organ and even each vertebra is marked as a separate object and highlighted in a specific color. [10]

In addition to the main three, there are other tasks in the resume, such as recognition and generation. Recognition is a comparison of an image with already known



samples, for example, identifying a person in a photo. Generation is creating new images based on existing ones.

The generation task is also used in medicine, mainly to train new models. High-quality medical data for training algorithms is scarce, and its preparation takes a lot of time. Therefore, data is artificially created based on existing data using generative algorithms.

All of the above tasks are often solved not separately, but together. For this, several models are combined into a cascade - a chain that sequentially performs a given set of actions. For example, it first detects an object, then classifies or recognizes it:

- detection shows the location of the tumor in the image and highlights this area of the image;
- classification determines whether the tumor is likely to be malignant;
- segmentation finds its exact boundaries;
- Recognition matches the tumor type with those known to the model with a certain accuracy.

. Results

Our analysis identifies five major application domains for computer vision in medicine:

Medical Imaging and Diagnostics

CV is used to detect anomalies in MRI, CT, X-ray, and ultrasound images. For example, convolutional neural networks (CNNs) can outperform radiologists in identifying early-stage pneumonia, tuberculosis, and brain tumors.

Histopathology and Cancer Detection

High-resolution slide images are processed to classify cancerous cells. Deep learning frameworks such as EfficientNet show 95%+ accuracy in breast cancer detection.

Surgical Navigation and Assistance

Augmented reality combined with CV guides surgeons during complex procedures, reducing human error and improving safety.

Patient Monitoring and Elderly Care

Computer vision integrated into cameras and wearables can detect patient movements, falls, facial expressions (pain recognition), and sleep patterns.

Administrative and Documentation Automation



Optical Character Recognition (OCR) technologies powered by CV automate the digitization and classification of handwritten and scanned medical records.

Discussion

The results affirm that computer vision significantly enhances diagnostic accuracy and procedural efficiency. However, challenges such as **dataset bias**, **interpretability of deep learning models**, and **regulatory constraints** remain unresolved. In low-resource settings, the implementation of these technologies requires careful consideration of infrastructure and training needs. Moreover, ethical concerns about patient privacy and algorithmic transparency must be addressed before full-scale deployment.

Conclusion

Computer vision holds transformative potential for modern medicine by automating complex tasks, minimizing human error, and facilitating early disease detection. To realize its full benefits, multi-disciplinary collaboration among engineers, clinicians, and data scientists is essential. Future research should focus on developing explainable AI models, securing large annotated datasets, and validating CV applications in real-world clinical environments.

The introduction of computer vision technologies in medicine is increasing the accuracy of diagnosis, real-time monitoring of patient conditions, and bringing the efficiency of the healthcare system to a new level. These technologies are a convenient tool for doctors, reducing their workload, reducing the number of errors, and playing an important role in protecting human health. In the future, computer vision is expected to be more widely used in the medical field with the help of systems that are deeply studied, enriched with data, and comply with information security requirements.

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