A STUDY ON AI MODELS FOR MULTI-DISEASE DIAGNOSIS USING STRUCTURED CLINICAL DATA

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Abstract: *In this work, I examine how artificial intelligence can help doctors understand the huge amounts of clinical information that accompanies allergic, neurological and cardiovascular diseases. At first glance, these three areas are almost unrelated to each other, but in fact they have an important common feature: each of them forms a large amount of structured data - laboratory parameters, examination results, clinical records, symptom dynamics and many small details that are easy to overlook in real practice. It is difficult for a person to process such information immediately, but for AI, the search for patterns in complex data sets is a familiar task.*

In our study, I analyse how different models of artificial intelligence - from classical machine learning methods to deep neural networks - apply to three groups of diseases. In allergology, AI helps to recognise the types of sensitisation and predict the reaction to therapy in advance. In neurology, models are able to analyse EEG, brain images and slow cognitive changes that develop over the years. In cardiology, AI supports doctors in detecting arrhythmias, assessing the functional state of the heart and predicting risks. In all three areas, predictive algorithms allow you to notice changes earlier and select treatment more accurately and individually.

At the same time, I emphasise that artificial intelligence is not a magical replacement for a doctor. Its effectiveness depends on the quality of the data, and the application requires caution and control by specialists. But in general, it becomes clear: AI is gradually becoming an important tool of modern medicine. It does not take the job away from the doctor, but helps to see the full picture, combining data and facilitating timely, balanced decisions.

INTRODUCTION

In recent years, the amount of medical data has grown so much that modern diagnostics is less and less based only on the experience of the doctor and more on accurate numerical indicators. Huge arrays of structured information are formed daily in hospitals: blood test results, ECG, vital signs, ultrasound and tomography data, as well as electronic medical records. When such data is collected in one format, they make it possible to use artificial intelligence (AI) not just as an additional tool, but as real support in diagnostics.

Machine and deep learning models are able to find patterns that a doctor may simply not notice - not because he is not experienced enough, but because the amount of data is too large for manual processing. AI is able to analyse hundreds of parameters at once, compare them with thousands of cases and give clues that help detect the disease at an early stage or clarify the diagnosis.

As part of our work, I decided to see how AI copes with the diagnosis of different groups of diseases, using structured data. I have chosen three directions that are very different from each other:

- Allergic diseases, where immunological indicators and individual reactions are important.
- Neurological diseases that require analysis of brain signals, images and clinical tests.
- Cardiovascular diseases, where ECG, echocardiography and heart parameters play a key role.

Comparing these three areas allows you to see how flexibly AI can adapt to completely different types of data and how much it really helps in diagnostics. Our goal is to show which algorithms work best, what difficulties arise in each area and why structured clinical data are so important for accurate and modern medicine.

2. AI FOR MULTI-DISEASE DIAGNOSIS: ALLERGIC DISEASES

When it comes to heart disease, the first thing that comes to mind for most people is their danger. Heart disease really remains one of the leading causes of mortality in the world, and that is why early, and accurate diagnosis is so important. In recent years, medicine has changed a lot: doctors are increasingly relying not only on their experience, but also on data - a large number of structured indicators that are collected automatically. These include ECG, test results, echocardiography, pressure and oxygen saturation, medical history, drug data and even some numerical parameters from medical images.

It is against this background that artificial intelligence began to play an increasingly prominent role. He can view and analyse huge amounts of data faster and more accurately than a person, especially when it comes to subtle changes in heart rhythm or combinations of biomarkers that are difficult to notice manually. With such a large amount of information, the doctor needs time, and the model can process it in seconds.

2.1 Why structured data is so important in cardiology

Heart disease, despite their prevalence, often manifests itself in different ways in different people. Sometimes everything seems obvious - severe chest pain, characteristic changes on the ECG. But in most cases, the disease develops gradually, and at first the signs may be invisible. This is where structured data gives an advantage: they record small deviations that accumulate over time.

For instance:

- ECG can show barely noticeable changes in the electrical activity of the heart.
- Blood tests can reveal an increased level of troponin or BNP.

- Echocardiography may indicate a decrease in the release fraction.

For a doctor, all these figures require careful interpretation. But for AI, it's just a set of features that it compares with thousands of other cases.

Thanks to this, models can "notice" even weak patterns that predict the early stages of heart failure or the risk of heart attack.

2.2 What AI models are used to diagnose heart disease

Different types of artificial intelligence models are used in cardiology, and each of them helps to solve specific problems in its own way.

Classic ML-models

They work well with structured tables and numerical data.

- Random Forest - often predicts the risk of complications after operations.
- XGBoost is one of the best algorithms for predictive models.
- SVM - copes well with the recognition of arrhythmias on the ECG.
- Logistic Regression - used as a basic tool for assessing the risk of heart attack.

These models are easy to learn and interpret, which makes them convenient for clinical systems.

Deep learning

This is where the most interesting possibilities of AI begin.

- CNN analyses ECG almost like an image - they notice the shape of waves, segments, intervals.
- RNN and LSTM work with time series and help to recognise patterns in the sequence of heartbeats.
- Transformers can take into account a large number of features at once and make more complex conclusions.

It is the deep models that show accuracy comparable to cardiologists, and sometimes higher, especially in ECG analysis.

2.3 How AI helps in the diagnosis of specific heart diseases

Here are some examples where models are really useful.

1. Myocardial infarction (MI)

AI often recognises a heart attack faster than a doctor.

For example, CNN can catch minimal changes in the ST segment, which are similar to noise, but actually indicate the onset of ischaemia.

2. Arrhythmia

Models are trained on millions of heartbeats.

They can distinguish:

- Atrial fibrillation,
- Extrasystoles,
- Tachycardia.

And they do it at high speed.

3. Heart failure

It is difficult to predict its development, but AI combines indicators from analyses, ECG and echocardiography and finds combinations of signs that indicate deterioration of the condition.

2.4 AI in cardiac surgery: how technology helps before, during and after surgery

Cardiac surgery is one of the most difficult areas of medicine. Any heart surgery is highly risky, and even small deviations can greatly affect the outcome. Therefore, surgeons always need the most accurate information. Here AI also begins to take its place, and in some tasks it already fulfils the role of the "second eye" of the doctor.

Preoperative evaluation

Before any heart surgery, doctors need to understand how ready the patient is, what complications are likely and what type of intervention is best suited. AI helps to analyse patient data collected over several years:

- ECG,
- Echocardiography,
- Blood tests,
- Data on chronic diseases,
- History of operations.

The model can compare this data with thousands of other patients and deduce an approximate risk. Such a prognosis does not replace the doctor, but helps to take into account factors that are difficult to recognise manually.

For example, XGBoost or Random Forest are often used to predict complications after coronary artery bypass. The model can suggest which patient has a higher risk of bleeding or arrhythmias after surgery.

During the operation

In the operating room, the heart is given maximum attention, and any changes should be noticed immediately. Usually a large team does this: a surgeon, an anaesthesiologist, monitoring specialists. AI can be an additional assistant.

He analyses:

- Change of rhythm,
- Blood oxygen saturation,
- Pressure,
- The work of artificial blood circulation (if it is used).

If the indicators begin to deviate from the norm, the model may issue a warning. So the doctor reacts faster than he would have noticed the changes manually.

In addition, studies show that AI can predict a pressure drop or arrhythmia a few minutes before it happens. This is critically important in cardiac surgery, where every second counts.

Post-operative period

After the operation, the patient is usually in intensive care for some time. The heart can react to surgery in different ways:

- Sometimes an infection develops,

- Rhythm disturbances may appear,
- There is a risk of re-bleeding,
- There is a possibility of deterioration of heart function.

AI can analyse postoperative indicators in real time and help predict complications in advance. For instance:

- Increased risk of sepsis,
- The probability of developing acute heart failure,
- The need for a repeat operation.

Some models do this more accurately than standard risk scales.

2.5 Application of AI in specific cardiological tasks

To make it clearer, here are some examples where AI really helps in diagnosis and treatment.

1. Myocardial infarction recognition

Infarction can manifest itself in different ways. Sometimes the symptoms are classic, sometimes they are blurred. AI trained on huge ECG arrays is able to catch even weak signs of ischaemia, which a person can mistake for an interference or artefact.

Some models show accuracy above 90%, which makes them useful in emergency rooms and emergency rooms.

2. Evaluation of heart function by echocardiography

Echocardiography is one of the most important diagnostic methods, but the quality strongly depends on who conducts the study. AI helps:

- Automatically measure the ejection fraction,
- Identify a violation of the movement of the heart walls,
- Analyse the dimensions of cameras.

This equalises the quality of diagnostics between different doctors and hospitals.

3. Determination of the risk of arrhythmias

Arrhythmias can appear suddenly, but there are usually hidden signs.

AI tracks the features of the rhythm and can:

- Identify the risk of atrial fibrillation,
- Detect unstable rhythms,
- Analyse cardiograms from watches or bracelets.

Such models make diagnostics more accessible and faster.

4. Prediction of heart failure

The combination of data - analyses, ECG, drugs, age, concomitant diseases - allows AI to predict deterioration in days or even weeks.

This helps to intervene in advance and avoid hospitalisation.

2.6 Limitations and difficulties of using AI in cardiology

Although AI sounds like an ideal solution, things are much more complicated in real medicine. Much depends on what data the hospital collects, how complete it is and how well the system can work with different patients.

1. Different data standards

Each hospital uses its own ECG machines, its own ultrasound protocols, its own resuscitation monitors. Therefore, the same disease can look different in different systems. AI trained in one clinic sometimes does not work well in another - simply because the data looks different.

2. Lack of large and high-quality datasets

Heart data is not always easy to collect. Especially if these are complex cases or rare complications. To train the model, you need thousands and tens of thousands of examples - and they are not everywhere. Because of this, algorithms are sometimes retreached and lose accuracy on new data.

3. Opacity of deep models

4. Some models, especially neural networks, work like a "black box". They give an answer, but the doctor doesn't always understand why. And in cardiology it is critical - the patient's life may depend on the decision. Therefore, doctors require the explanability of the models.

4. Risks of errors and legal liability

If AI made a mistake, who is to blame? Programmer? Doctor? Hospital?

There is no clear answer to these questions yet, and this hinders the introduction of technologies.

5. Hospital integration

Even if the model is excellent, the hospital needs equipment, computers, staff training. And not every clinic is ready for such changes.

2.7 Ethical issues

Even when AI works well, there are moments that cannot be ignored.

Patient confidentiality

Cardiological data is very sensitive. ECG, tests, diagnoses - everything should be stored safely. Leaks should not be allowed.

Fairness and lack of bias

If the model was trained in one region, it may work worse for people of a different nationality, age or gender. This can lead to wrong diagnoses.

Informed consent

The patient should understand that part of the diagnostics is performed by AI. It's a matter of trust.

2.8 The future of AI in cardiology and cardiac surgery

In the coming years, AI will become part of almost every stage of heart disease treatment.

1. Fully automatic ECG interpretation

The models will not only recognise arrhythmias, but also predict heart attacks, analyse electrolyte balance according to the cardiogram and see deviations even before the symptoms appear.

2. Smart devices for rhythm tracking

Smart watches, fitness bracelets, implants will transmit data to AI systems that automatically analyse the heart rate and warn of risks.

3. Improved echocardiography

AI will completely decipher the ultrasound of the heart:

- Measure the ejection fraction,
- Evaluate the valves,
- Identify ischaemia,
- Predict the development of heart failure.

4. Assistance to robots during operations

In the future, AI will be able to tell the surgeon where it is better to make an incision, which bypass technique is suitable for a particular patient and what actions will lead to the best result.

5. Personalised treatment

Based on hundreds of parameters, AI will be able to offer individual therapy regimens that are suitable for this patient, and not "on average".

2.9 Brief summary of the chapter

AI really changes the approach to the diagnosis and treatment of heart disease. His strength is that he is able to work with a huge amount of structured data - ECG, blood tests, echocardiography, resuscitation indicators. It is difficult for a person to process this amount of information manually, and the model copes in seconds.

AI helps:

- Detect a heart attack earlier,
- Better to interpret arrhythmias,
- Calculate the risks before operations,
- Monitor the patient's condition after the intervention,
- Support doctors during complex operations.

Of course, there are limitations: lack of quality data, differences between hospitals, difficulty in explaining the solutions of the model.

But as technology develops, AI becomes an increasingly reliable and useful tool that does not replace doctors, but helps them work more accurately and faster.

3. AI FOR MULTI-DISEASE DIAGNOSIS: ALLERGIC DISEASES

Allergology is an area where data plays almost as important a role as the patient's symptoms. Each person reacts to allergins in their own way, and doctors have to take into account dozens of factors: IgE levels, skin tests, combination of allergies, seasonality, heredity, concomitant diseases. All this turns into a huge array of information that is difficult to interpret manually. That is why artificial intelligence methods are becoming more and more in demand - they are able to notice non-obvious connections and patterns where human analysis is no longer effective.

3.1 Classical Machine Learning Models

Classic machine learning models are what started the introduction of AI into medical analytics. They work with tabular clinical data and allow doctors to better understand the structure of the disease.

3.1.1 Decision Trees

Decision Trees are often used to identify key predictors of allergies. They analyse:

- Levels of specific IgE,
- Dimensions of skin samples,
- The severity of symptoms,
- Features of the anamnesis.

The most valuable thing in such models is transparency. The tree shows why this or that conclusion was made. The doctor literally sees the "logical path" of the algorithm: what parameters played a role and why the model decided that the risk of high sensitisation or reaction increases.

3.1.2 Random Forests

Random Forest is an improved version of the decision tree. Here, many trees work together at once, compare the results and eventually give a more stable and reliable forecast.

Such models are used for:

- Determination of the type of sensitisation (mono-, poly-, cross),
- Assessment of the probability of a clinical reaction to an allergin,
- Prediction of the result of allergin-specific immunotherapy,
- Identification of patients with a high risk of severe allergic episodes.

Random Forest copes well even with situations where the data is heterogeneous, and some indicators are rare - which is typical for allergology.

3.1.3 Clustering Algorithms

Clustering allows you to group patients not by formal features, but by their true immunological patterns.

Such algorithms identify:

- Monosensitised,
- Polysensitised,
- Cross-reacting patients,
- Hidden phenotypes that cannot be noticed without mathematical analysis.

This helps doctors better understand the nature of the disease and develop more personalised approaches. For example, two outwardly similar patients may have completely different mechanisms of an allergic reaction - and, accordingly, different optimal treatment regimens.

3.2 Deep Learning Models

If classical models work well with familiar clinical tables, deep learning is able to analyse complex, unstructured data: skin images, text records in medical records, time series and much more.

This area is developing the fastest today.

3.2.1 Medical Imaging Analysis

In case of skin allergic reactions, the appearance of the affected area is an important diagnostic clue. However, the doctor's eye is limited, and the assessment may depend on experience.

Deep neural networks - especially CNN - analyse:

- Photos of atopic dermatitis,
- Elements of the rash,
- Centres of urticaria,
- Spots, erythema, inflammation levels.

Models notice the smallest details - a change in skin texture, colour, lesions - and do it objectively and equally for all patients. Thanks to this, diagnostics becomes more standardised.

3.2.2 Electronic Health Record (EHR) Analysis

A patient with allergies can be observed for years. The accumulated information includes:

- Results of dozens of analyses,
- IgE dynamics,
- Reaction to different allergens,
- The influence of the season,
- Effectiveness of past treatment methods.

Deep models - RNN, LSTM, Transformers - are able to analyse such time series and find patterns that are difficult for a person to recognise.

For instance:

- Increased risk of exacerbations before a particular season,
- The connection between stress and the severity of allergies,

Relationships between several allergies at the same time.

3.2.3 Immunological Reaction Forecasting

Deep models also help to predict the patient's future reactions.

They take into account:

- Clinical data,
- Laboratory parameters,
- Genetic predisposition,
- Features of previous reactions.

Such models are able to estimate the probability of:

- Severe reaction to a specific allergin,
- The success of immunotherapy,
- The need to adjust the current treatment.

AI can "notice" the patterns that are hidden behind dozens of factors and tell the doctor in advance that it is worth changing the therapy plan.

Predictive Risk Modelling and Personalised Treatment

One of the most useful applications of AI is predicting the risk of developing allergic diseases and personalising treatment.

This is especially important in paediatrics. In children with atopic background, models help to evaluate:

- The probability of developing asthma,
- The risk of atopic dermatitis,
- The strength of the future reaction to a specific allergin,
- The recommended observation tactics.

For adults, AI helps:

- To select individual treatment regimens,
- Evaluate the effectiveness of pharmacotherapy,
- To predict seasonal exacerbations,
- Prevent severe episodes through early warning.

Such personalisation makes the treatment more accurate and the patient's life more comfortable.

3.3 Advantages and Limitations of AI in Allergology

3.3.1 Advantages

- High accuracy of sensitisation assessment;
- The possibility of early detection of allergies;
- Individualisation of treatment;
- Quick decision-making;
- Objectivity, absence of subjective mistake of the doctor;
- The ability to detect connections between dozens of factors at the same time.

3.3.2 Limitations

- The quality of the model depends entirely on the quality of the data;
- High requirements for the protection of personal information;
- Deep models are often difficult to interpret;
- In case of data imbalance, the model can give erroneous forecasts;
- Ethical questions are possible when using children's data.

4. AI IN NEUROLOGICAL DISEASE DIAGNOSIS

Neurology has always been an area where even experienced doctors have to work literally "between the lines". The brain is a very complex structure, and it does not always show its problems openly. The images may not show early damage, EEG may look almost normal, and cognitive changes often develop so slowly that the patient or his family notice them only after years. All this makes the diagnosis of neurological diseases very difficult. That is why artificial intelligence has gradually taken an important place in this area.

AI is able to analyse long time series, images, speech patterns, behaviour and clinical records, noticing subtle signals that easily escape the human eye. And although the doctor makes the final decision, the models become a reliable assistant for him: they show what was previously impossible to see.

4.1 Classical machine learning models in neurology

Before deep neural networks became popular, classic ML models were actively used in neurology. They worked (and continue to work) with structured data: EEG parameters, memory test results, speech tests, age, medical history, examination results and many other characteristics.

Despite their relative simplicity, such models help to recognise patterns in epilepsy, Parkinson's disease, dementia, the consequences of stroke and other diseases where the human gaze faces limitations.

4.1.1 Logistic Regression and Support Vector Machines

Logistic regression and SVM are models that work well where you need to understand the logical structure of the disease. In neurology, they are used, for example, to:

• assess the risk of epileptic seizure,
• identify mild cognitive disorders,
• distinguish normal ageing from early dementia,
• determine the likelihood of developing Alzheimer's disease.

They are easy to interpret, which is especially important in medicine: the doctor needs to understand why the model makes a conclusion. Therefore, these methods remain relevant, especially where there is little data and decisions need to be made quickly.

4.1.2 Random Forest and Gradient Boosting Models

Random Forest and gradient boosting models have proven to be surprisingly effective for analysing complex clinical data - those where there are many variables, and each can affect the patient's condition.

These models help:

• classify the types of epileptic activity,
• predict the probability of a second stroke,
• assess the severity of Parkinson's disease,
• analyse combinations of factors affecting cognitive decline,
• predict the patient's response to drug therapy.

The advantage of these models is that they are able to explain which signs have become key. For example: what EEG indicator, what change in movement or which cognitive test played a decisive role in the prediction.

4.1.3 Clustering in search of hidden phenotypes

One of the most interesting areas is clustering. It allows you to see groups of patients who look similar, but are sick in different ways.

In real practice, it looks like this:

• in Parkinson's disease, it is possible to distinguish patients with a predominance of tremor, with pronounced rigidity, with rapid progression of the disease;

• in epilepsy, subtypes with a high frequency of seizures, with hidden triggers or with an unusual reaction to therapy are distinguished;

• in dementia, algorithms see subgroups with different rates of memory and speech deterioration.

This division helps doctors to choose treatment more accurately and in a personalised way.

4.2 Deep learning in neurological diagnostics

When complex data appears - long EEG, brain images, speech, movements - it is the deep neural networks that show the best result.

Neurology was one of the first areas where deep learning began to bring real clinical results.

4.2.1 EEG analysis using CNN, LSTM and Transformers

EEG is a chaotic, changeable signal that is difficult to read even for experienced specialists. AI does it differently:

• CNN analyses spectral maps,
• LSTM track long-term changes,
• Transformers recognise complex time patterns.

Models can:

• determine epileptiform activity,
• predict the probability of an attack,
• identify sleep disorders,
• monitor the patient's reaction to anticonvulsants.

This is especially important in intensive care, where EEG is recorded for hours and it is unrealistic for a person to see everything.

4.2.2 Deep MRI and CT analysis

Brain pictures contain thousands of small details. In the early stages of the disease, some injuries are too small to be noticed manually.

Deep neural networks are able to recognise:

• microfoci of ischaemia,
• atrophy of the cerebral cortex,
• small tumours or their changes,
• damage to the white matter,
• traces of inflammation or demyelination.

Such models become especially important in multiple sclerosis, dementia and post-traumatic brain injuries.

4.2.3 NLP analysis of speech and clinical records

Speech is one of the most accurate reflections of the brain. It changes even before noticeable clinical symptoms appear.

AI analyses:

• pace of speech,
• changes in intonation,
• the length of the pauses,
• vocabulary wealth,

• grammatical structure of sentences.

It helps:

• identify early signs of dementia,
• distinguish depression from cognitive disorders,
• track the progress of Parkinson's disease,
• control the dynamics of neurological symptoms.

4.3 Prognostic models and prognosis of the course of the disease

One of the strongest applications of AI is forecasting. In neurology, many diseases develop slowly, and if you know in advance the trajectory of their progression, you can intervene in time.

AI helps to predict:

• the probability of a second stroke,
• risk of an epileptic seizure,
• the rate of progression of Parkinson's disease,
• probability of memory impairment,
• transition of mild cognitive disorders to dementia.

Such models give doctors something that was not there before: the opportunity to see the disease ahead.

4.4 Personalised neurotherapy and rehabilitation

Artificial intelligence is gradually becoming an assistant in the choice of therapy.

It helps:

• select more accurate dosages of medicines,
• create individual rehabilitation programs depending on the type of violation,
• predict which exercises will most effectively restore speech or movement,
• track the dynamics of recovery after a stroke.

This makes the treatment not only accurate, but also milder for the patient.

4.5 Advantages and limitations of AI in neurology

4.5.1 Advantages

• sees what is inaccessible to humans;
• speeds up diagnostics;
• helps in early detection of diseases;
• makes predictions on the course of the disease;
• creates individual therapeutic plans;
• analyses large volumes of EEG and MRI without fatigue.

4.5.2 Restrictions

• models depend on data quality;
• deep models are difficult to explain to doctors;
• sometimes there is a lack of marked neural data;
• strict protection of personal information is required;
• different clinics use different examination protocols.

COCLUSION

In the course of our work, I tried to look at medical diagnostics not only from the point of view of doctors, but also through the prism of modern technologies. Today, artificial intelligence has ceased to be something "experimental" - it is gradually becoming part of ordinary clinical practice. And this is best seen in the examples I have chosen: allergic, neurological and cardiovascular diseases. Despite the fact that these three directions are very different, they have one thing in common - a huge amount of structured data that is constantly collected and can be used to improve diagnostics.

In each of these areas, AI manifests itself in different ways. In allergology, it helps to analyse immune reactions and detect patterns that are difficult to see manually. In neurology, models work with signals, images and complex clinical tests, recognising even weak deviations in the nervous system. In cardiology, AI helps to identify heart attacks, arrhythmias, assess risks and even support doctors during operations. That is, with all the differences, the principle is one - big data allows models to notice what is difficult for a person to process at once.

But it is important to understand that AI does not replace a doctor. It only enhances its work, helps to make decisions faster and reduces the likelihood of error. At the same time, difficulties remain: lack of quality data, difference in standards between hospitals, issues of ethics and responsibility. All this means that technologies should be implemented carefully and gradually, not forgetting about human control.

In general, our study shows that the use of AI in diagnostics is not just a trend, but a real step forward. Structured clinical data give it the basis, and the variety of diseases is a field for development. With the right approach, such technologies can make medicine more accurate, faster and accessible, while maintaining the main goal of improving the quality of life of patients.

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