# HeartUp: Diagnosing and Monitoring Heart Failure with Multi-Modal Data

*A web-based end-to-end management system integrating multi-input machine learning models to aid cardiologists in their practice

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***Abstract*—This paper presents HeartUp, an innovative cardiology management system designed to enhance the diagnosis and monitoring of heart failure (HF) conditions, which currently affect 26 million patients worldwide. Heart failure management is often hindered by delayed treatment and insufficient monitoring despite the availability of extensive patient data, leading to severe and sometimes fatal outcomes. HeartUp addresses these challenges by integrating and processing various forms of essential cardiac diagnostic data, including medical forms, heart sound recordings, and electrocardiograms (ECG). The system also evaluates the feasibility of using left ventricular assisting devices (LVADs) for individual patients. LVADs, although beneficial for regulating blood flow, are hampered by high manufacturing and maintenance costs, making their widespread use problematic. HeartUp's comprehensive management solution leverages multi-modal data inputs—such as audio, echocardiography, imaging, and laboratory analyses—to provide cardiologists with a robust tool for assessing patient conditions and making informed decisions regarding the viability of LVAD deployment. By streamlining the storage, processing, and reporting of cardiac health data, HeartUp aims to improve the quality of care and patient outcomes in cardiology by facilitating timely and accurate treatment interventions.**

***Index Terms*—Deep Learning, Healthcare Data Science, ECG, EchoNet Dynamic, Echocardiography**

## I. Introduction

Heart failure (HF) is affecting 26 million patients worldwide [1]. Every year, approximately 550,000 new cases of heart failure are recorded only in the US [2]. Heart failure among all other diseases is also considered as one of the most lethal and most patients who experience HF often encounter comorbidity including immunodeficiency, diabetes or blood clots. Taking all this into account, patients become obliged to be constantly monitored by cardiologists to prevent further negative outcomes and new cardiac complications. [3].

The lack of immediate treatment, recovery and constant monitoring of post- and pre-HF conditions despite the availability of vast amounts of data mostly lead to the complicated cases and even lethal outcomes [4].

The modern approach of patient care relies on manual diagnostics and the usage of proprietary systems. After several problem interviews with the National Cardiac Surgery Center in Astana, it was discovered that the currently used system called "PACS" is only able to examine the necessary markers and condition statistics without actually assisting the cardiologist in data-driven decision making [5].

A lot of heartbeat, ECG, echocardiography, and lab analyses data is not used in hospitals around the world and is either deleted or just accumulated over the years, taking terabytes of data storage. This data can be used to train machine learning models that can aid cardiologists in diagnosing patients based on many analytical and computational features, thus being helpful in increasing the likelihood if positive health outcomes.

Left ventricular assisting devices (LVAD) are the supporting gadgets necessary for the regulation of the blood flow artificially [6]. However the manufacturing and maintenance costs required make the distribution of the LVADs problematic [7]. That is why, it becomes necessary to objectively evaluate the medical records of the patients and assess the viability of attaching LVAD based on all the data affiliated with the patient [7].

We propose HeartUp - an end-to-end cardiology management solution for cardiologists to assist the process of making the diagnosis based on multi-input data including audio, echocardiography, image, and lab analysis information about the patient's cardiac well being.

HeartUp is an end-to-end cardiovascular patients management and tracking system developed with clinicians in mind.

The project focuses on providing easy-to-use dependable and robust services.

HeartUp features CRM-like functionalities such as patient registration, patient tracking, appointments, patient analyses data saving. On top of that, there are four state-of-the-art machine learning models for prediction of various cardiovascular health-related diseases. Another important part of the system is the ability to create a comprehensive reader-friendly report consisting of the prediction data, patient history, and visual representations of most important health-related features.

The primary contributions of this paper are outlined as follows: it presents HeartUp, a cardiology management system designed to enhance the diagnosis and monitoring of heart failure (HF), a condition impacting 26 million people worldwide. HF management frequently faces challenges such as delayed treatment due to the underutilization of patient data, which can lead to severe consequences. HeartUp addresses these issues by integrating and processing a wide range of cardiac data, including medical forms, heart sound recordings, and electrocardiograms (ECG), and it evaluates the viability of using expensive left ventricular assisting devices (LVADs). Utilizing multi-modal data sources such as audio, echocardiography, imaging, and laboratory analyses, HeartUp equips cardiologists with a robust tool for making well-informed decisions. Ultimately, HeartUp aims to improve patient care by enabling more timely and precise interventions in cardiology.

The organization of this paper is structured to provide a thorough overview of the development and effectiveness of HeartUp, a cardiology management system. The paper begins with a review of the background and related work, highlighting the current challenges in heart failure management and the technological advancements in cardiology. This is followed by a detailed discussion of our project approach, where we explain the methodologies and theoretical frameworks that guided the system's development. Next, the project execution section describes the practical steps taken to implement HeartUp, including the integration of various diagnostic data sources. The evaluation section then assesses the system's performance through testing and real-world applications to validate its efficacy in improving diagnostic accuracy and patient management. Finally, the paper concludes with a summary of our findings and discusses potential future research and enhancements to further develop and refine the system's capabilities.

## II. Background and Related Work

Over the years, many other researchers and companies proposed and implemented Machine Learning models and systems for cardiology patients. However, the overwhelming majority of said solutions lack have downsides - some systems focus solely on one problem at a time, others are manual-input and manual-work based and are slow and inefficient. We will discuss one example from each category below.

### *A. Ukranian alternative system*

More than ever, Ukrainian manufacturers are producing digital electrocardiographic telemetry systems. Electrocardiograms (ECGs) can be recorded by these devices and sent to distant diagnostic facilities. The "Telecard" developed by the "TREDEX Company" in Kharkov, Ukraine, is one noteworthy system. It can send ECGs over radio, mobile networks, and regular phone lines, among other means of data transfer. Since ECGs are transmitted digitally, high-quality signals are guaranteed for remote cardiac condition diagnosis. This emphasizes how modern telemetry systems must include smart cardiac decision support systems (CDSS) to improve the accuracy of diagnoses in medical crises [8]. However, the downside is that the system is focused only on one type of data and does not feature any computational analytics based on ECGs.

### *B. Machine learning with the Electronic Health Records*

In this study, researchers improved their ability to predict with more accuracy whether patients will survive following an echocardiography by utilizing sophisticated computer approaches. In the past, physicians mostly used indicators like as ejection fraction (EF) and other medical conditions to create these forecasts. Nevertheless, the goal of this study was to determine whether improving the survival prediction by combining additional health information with more precise heart parameters from echocardiograms.

They examined information from a sizable patient base that had echocardiograms at a local healthcare facility. They contrasted the accuracy of various computer models' survival predictions with the conventional techniques.

Three sets of data were used: 1) basic health information such as age, sex, and heart rate; 2) the same information along with the doctors' measured EF; and 3) all of that information along with an additional 57 heart measurements from the echocardiography. They also used a unique computer technique to fill in any missing data.

The outcomes demonstrated how much more accurate the computer models were than the conventional techniques at predicting survival. The most accurate models were the random forest ones. The best estimates were obtained by including all of the specific cardiac measures. Interestingly, they discovered that certain cardiac parameters, such as tricuspid regurgitation velocity, were even more useful in predicting survival than EF [9].

Although this research project is an impressive feat of technology, the downside to the project is the fact that it is not a ready-to-use user-friendly service. Moreover, it does not include heartbeat audio data. Even though it shows great results and is robust and reliable, it cannot be used by people that do not know how to write code - it is not usable for an average clinician.

## III. Project Approach

To optimize the tasks facilitation within the development team it was concluded to split the project into 2 consecutive parts: machine learning models and web development part.

The decision of splitting the tasks in that way made it possible to get the tasks done in "agile" way with optimally distributed tasks and duties.

### *A. Machine Learning part*

The machine learning team focused on the diversification of the heart disease classification capabilities that could expand the range of cardiovascular health issues diagnostics. Therefore, the project features a combination of four machine learning models with different kinds of data at the input and different health conditions predictions as output.

Main libraries for the machine learning part were TensorFlow2, Keras, Pytorch, numpy, librosa, and pandas. Matlab was also used for the UCI dataset.

All models were deployed using FastAPI server endpoints on different machines for optimized inference speeds. After deployment, each model was released online using free Ngrok servers. All of the models are up and running in Professor Adnan's lab in C4 block.

Fig. 1. One of the servers running the project backend

*1) Dataset of University of California, Irvine (UCI):* Every patient had experienced a heart attack at some point. While some are still living, others are not. When combined, the survival and still-alive variables show whether a patient lived for a minimum of a year after having a heart attack.

Predicting whether or not the patient will survive for at least a year based on other variables was the issue that previous researchers attempted to solve.

The dataset comprises of 10 features with multivariate data and the data donation was conduced at the University of California, Irvine in 1989. The structure of the variables in the dataset are present in the Table 1.

TABLE I
UCI DATASET VARIABLES

| Variable Name | Role | Type |
|---|---|---|
| survival | Target | Integer |
| still-alive | Target | Integer |
| age-at-heart-attack | Feature | Integer |
| pericardial-effusion | Feature | Binary |
| fractional-shortening | Feature | Continuous |
| epss | Feature | Integer |
| Ivdd | Feature | Continuous |
| wall-motion-score | Feature | Continuous |
| wall-motion-index | Feature | Continuous |
| mult | Feature | Continuous |

*2) Electrocardiogram dataset of PhysioNet:* The PhysioNet/CinC Challenge 2017 is a competition to create algorithms that can identify different heart rhythms from short recordings (30-60 seconds) taken with a single sensor. The team has used the main deliverable of the challenge, its dataset with the electrocardiogram recordings with the variety of different heart rhythms.

The challenge focuses on atrial fibrillation (AF), a common irregular heartbeat. The algorithms need to distinguish between:

- Normal sinus rhythm
- Atrial fibrillation (AF)
- Other abnormal rhythm
- Too noisy to classify

This is difficult because short recordings can be noisy and some abnormal rhythms mimic AF. The competition hoped to improve algorithms for automatically detecting AF in real-time. 48 half-hour snippets of two-channel ambulatory ECG recordings from 47 people that the BIH Arrhythmia Laboratory analyzed between 1975 and 1979 are available in the MIT-BIH Arrhythmia Database. A total of 4000 24-hour ambulatory ECG recordings were obtained from a mixed population of patients at Boston's Beth Israel Hospital, consisting of approximately 60% outpatients and 40% inpatients. Of these recordings, twenty-three were randomly selected, and the remaining 25 recordings were chosen to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample.

Over a 10 mV range, the recordings were digitized at 360 samples per second per channel with 11-bit resolution. Each record was separately annotated by two or more cardiologists; differences were settled to produce computer-readable reference annotations for every beat (about 110,000 annotations total) that are included in the database. The dataset's profile with the information about the classes and their frequency in the recordings as well can be visible from the Table 2.

TABLE II
DATA PROFILE FOR THE TRAINING SET.

| Type | # recording | Mean | SD | Max | Time length (s) |
|---|---|---|---|---|---|
| Normal | 5154 | 31.9 | 10.0 | 61.0 | 9.0 |
| AF | 771 | 31.6 | 12.5 | 60 | 10.0 |
| Other rhythm | 2557 | 34.1 | 11.8 | 60.9 | 9.1 |
| Noisy | 46 | 27.1 | 9.0 | 60 | 10.2 |
| Total | 8528 | 32.5 | 10.9 | 61.0 | 9.0 |

Since PhysioNet's founding in September 1999, almost half of this database—25 of the 48 complete records and reference annotation files for every record—has been made publicly available. In February 2005, the remaining 23 signal files were made available here; previously, they were exclusively available on the MIT-BIH Arrhythmia Database CD-ROM. The examples of the ECG waveforms across different classes in the study can be seen from the Figure 1.

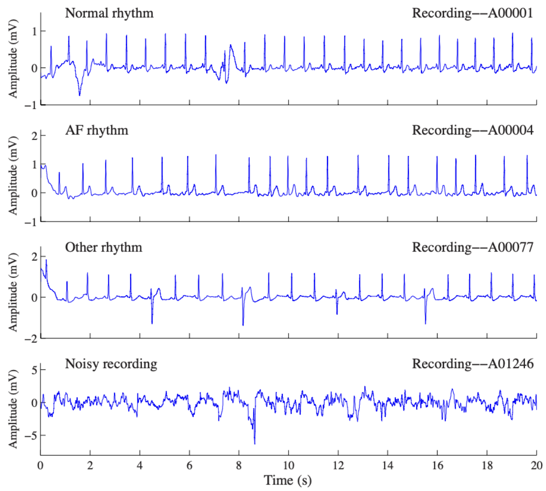


Fig. 2. ECG Waveforms of 4 distinct classes

*3) Heart sound dataset:* The heart sound dataset used for the project is the Isthethoscope Pro challenge from 2017. It consists of more than 800 labeled samples belonging to five classes: normal heartbeat, murmur, extra heart sound, extrasystole, and artifact [10]. Each sample is an audio of length from 1 seconds to 30 seconds. Some samples also have segmentation data for spectrogram heartbeat locations.

We applied a low-pass filter at 195 Hz to each training sample since most heartbeat audial data is contained in lower frequencies, while the higher frequencies contain noises [10].

The data was gathered in real-world situations using an Iphone app called Isthethoscope Pro [10]. Due to this, there is a variety of situations such as noisy environments, breathing, traffic, and others. This feature of data provides robustness to machine learning algorithms trained on it.

Our team has developed an LSTM-based deep neural network with Python library Keras with the TensorFlow2 backend for the classification of four classes in this dataset. F1 score for the validation dataset of 85% and classification accuracy of 88% were achieved.

*4) Echocardiography dataset:* The echochardiography dataset used for this project is called. It consists of 10,030 apical-4-chamber echocardiography provided Stanford University Hospital [11]. Each video in the dataset is downsampled to the resolution of 112x112 pixels and is put into the black-white mode, and each sample is anonymized and is linked to a person that went heart ultrasound procedure in the hospital in the period between 2016 and 2018. For these patients, left ventricular assisting devices (LVADs) have been installed to support their heart function [8].

LVADs are gadgets necessary for the regulation of the blood flow artificially [6]. However, installing LVADs is linked with future right ventricular issues, and these issues can be somewhat predicted using Ejection Fraction of the right ventricular [12].

We used the backbone of a third-party model EchoNet-Dynamic developed at Stanford in 2020 for training and deployment [11]. EchoNet is a state-of-the-art left ventricular semantic segmentation and ejection fraction calculation deep neural network that uses echocardiography videos as an input. On top of producing segmentation of the heart light ventricular, it also outputs the Ejection Fraction value for each sample. Ejection Fraction is the main health marker we use in our system. The model is based on the ResNet architecture and AUC of 0.92 and Dice similarity coefficient of 0.92 [11].

EchoNet was modified for deployment and for inference, since the initial model release was meant to be used as a Python script. On top of that, many dependency issues were solved and the whole model infrastructure and inference were lightened.

### B. Web-development part

Prior to the project development, we decided to follow a mixture of well-known Software Engineering Methodologies

User Center Design (UCD) - ensuring that the website is accessible and easy to use for both patients and hospital staff has been and remains our top priority.

Lean Development - while developing the website we were tempted to implement features that weren't required at the time or were of low importance. To mitigate these we decided to follow the principles of Lean Development and focused on the current tasks and features that were valuable at the current stage of the development.

Agile Development - as there were some ongoing uncertainties pertaining to some aspects of our project, Agile Development was deemed the most fitting considering its emphasis on flexibility and adaptability.

Component-Based Development - the choice of component-based development for front-end development of the system was made because it enhances re-usability of components. This type of development allows the creation of modular and scalable UI components. That is why the React.js was chosen as the main front-end development language.

## IV. Project Execution

The project changed drastically throughout the last two semesters. At first, we were focused on producing and releasing a new labeled echocardiography dataset with the aid of the National Cardiology Research Center (NCRC) and the development of a new semantic segmentation model on top of that. Echocardiography datasets are very uncommon to be released to open-source due to high processing and labeling times each sample requires. Unfortunately, we were not able to obtain data from the NCRC due to miscommunication and technical issues. Without new data, the initial project idea was not viable and simply could not be finished due to the new model requiring new data as an input.

Due to this, as per one of the initial contingency plans, the project focus was shifted from a dataset and a model to an end-to-end cardiology health analytics platform. Most of the work done in the first semester, namely the backend, the frontend, and model developments, were discarded, in favor of the new direction that the project has been set to take on.

After some research, negotiation, and brainstorming, the team settled on a new idea of an end-to-end user-friendly platform in late February. New contingency plan, functionality, website design, and three models were introduced to the project since.

*1) Frontend development:* Firstly, the team focused on developing the frontend, as it was the most challenging part of the project. The frontend for the project has been in development since late February until mid-April. New landing page, login page, patient history page, patient list page, model selection page, and other pages were developed and added throughout this period. Before that, the project had a more utilitarian focus without the need for the project to be accessible, now, however, the project adopted a new design philosophy to create an intuitive and user-friendly interface for cardiologists to use. This process involves careful consideration of user experience principles. Main routes within the front-end are implemented to ensure seamless navigation and interaction with the web application. React.js was chosen for the front-end development as it utilizes reusable components, is lightweight, and has strong community support. Moreover, React.js provides functionality to do data encryption and secure communication, which makes it even more suitable for highly confidential health-related information. Rapid experimenting with real-time change tracking was also extremely helpful in development.

*2) Backend and model APIs development:* Model training and model APIs were developed in parallel with the backend for the application between mid-February and mid-April. Each model was deployed using FastAPI server endpoints and is running on a separate machine.

The back-end of the web application is structured with main routes such as routes for prediction of tab form, prediction of audio, and so on, each serving a distinct purpose. The core logic behind the web app, which includes data processing, analysis, and interaction with models, is implemented in this phase to ensure robust functionality.

The back-end was implemented using the Python Django framework which provides a robust, secure, and fast-to-code environment. This framework is also known to be used in many apps that require high-throughput due to its scalable nature. On top of that, Django provides many useful services logic such as user authentication and login out-of-the box.

For the initial deployment and the Proof of Concept (PoC), the team has used the rapid model deployment tool called Streamlit [13]. The pre-trained machine learning models were deployed with the help of the ngrok service [14]. That allowed to get the application programming interface (API), send the necessary GET and POST requests to the models.

## V. Evaluation

For this project, evaluation was divided in the following manner: website evaluation (UI/UX and load times), evaluation of each model separately, evaluation of models based on single-patient data.

For the website evaluation part, we have let other people use the website to collect their opinion on website loading times and website usability. Based on the feedback we got from testers, we modified certain components of the site such as button placement and tables styling.

### A. Idea evaluation by cardiologists

A very important part of our project was understanding if our project has any merit to it. In order to find out if the work made any sense, we arranged six meeting with cardiologists from the National Cardiology Research Center in Astana, located at the Turan avenue. On top of obtaining any sense of direction, we also were planning on working in tandem with cardiologists to label more than 5,000 echocardiography videos from Kazakhstani patients and release them as a new dataset, possibly submit it to a medical machine learning conference.

Meetings proved to be successful and useful since we have gained lots of new domain-specific knowledge about the issues we were trying to solve. The feedback gained from meetings has also greatly helped in shaping the final project and choosing the actual direction.

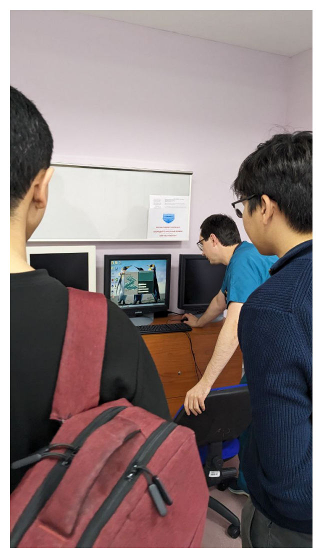

Fig. 3. One of the meetings with cardiologists

Unfortunately, obtaining echocardiography videos from NCRC has not come to fruition due to many technical, legal, and other reasons. Due to this, we decided to shift the project focus and went to cardiologists again.

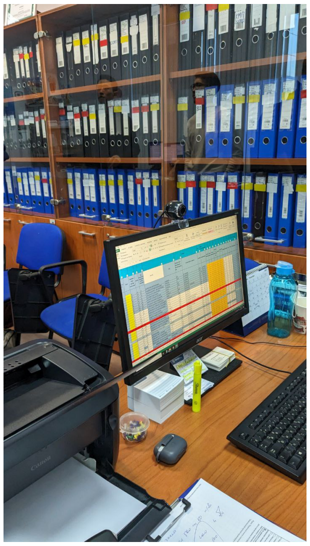

Fig. 4. Data about patients phenotype

Due to the work done and the positive feedback received from cardiologists, we concluded that the project focus should be on providing an end-to-end system for cardiac health tracking and analytics. We decided to focus on four models for different health diagnoses. Each model was firstly evaluated separately. Technical side of evaluation went well as all models performed correctly and showed great results. Below you can see separate tables for each model's performance.

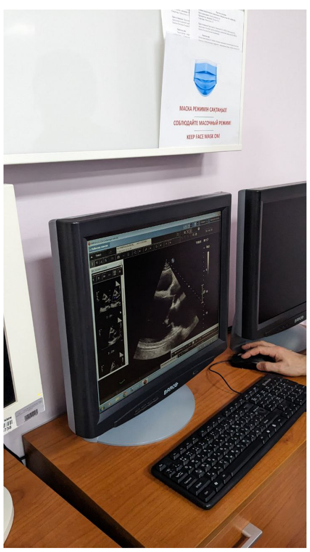

Fig. 5. A proprietary echocardiography system

### *B. Machine Learning models evaluation*

*1) UCI dataset models:* For echocardiograms, we did use several classification models on the UCI dataset after the initial preprocessing and exploratory data analysis. The results can be seen in the Table III.

TABLE III
UCI DATASET CLASSIFICATION MODELS

| **Model** | **Accuracy** |
|---|---|
| LogisticRegression | 84.62 |
| DecisionTreeClassifier | 89.74 |
| RandomForestClassifier | 92.31 |
| GradientBoostingClassifier | 87.18 |

*2) ECG dataset models:* As for the electrocardiogram dataset (ECG), the decision of was made to use the autoencoder neural networks. They can be used to learn informative hidden patterns from ECG data without needing pre-labeled heart rhythm classifications. This allows the model to capture the underlying structure of normal and abnormal heart rhythms. The summary of the performance can be represented in the Table IV.

TABLE IV
ECG CLASSIFICATION MODEL PERFORMANCE SUMMARY

| **Metric Name** | **Performance** |
|---|---|
| Accuracy | 75.72 |
| Precision | 53.87 |
| Recall | 88.03 |
| F1 Score | 66.84 |

*3) Heartbeat audio dataset models:* For heartbeat audio, the trained LSTM CNN-based model was validated on a holdout dataset that consisted of 5% of the initial dataset. Results of 88% and 87% for classification accuracy and F1-score, respectively, were observed for the holdout validation dataset. The model performed relatively similar on the test dataset, achieving F-1-score of 88.5% and accuracy of 89%. Since metrics for both test and validation dataset were close, the model performance was considered robust.

TABLE V
LSTM CNN MODEL PERFORMANCE SUMMARY

| **Metric Name** | **Performance, %** |
|---|---|
| Accuracy | 89 |
| Precision | 84 |
| Recall | 89 |
| F1 Score | 88.5 |

*4) Echocardiography dataset models:* For echocardiography videos, EchoNet was validated on the holdout validation dataset sized 2% of the original data. Since the initial dataset was not large and we had not obtained new data, only a small fraction of the initial dataset could have been used as holdout. IoU of 0.85 and AUC of 0.86 were achieved on the holdout validation dataset, while IoU of 0.86 and AUC of 0.86 were observed for the test dataset. Due to both IoU and AUC being corresponding for both validation and test dataset, the model training was considered successful and the performance counted robust.

TABLE VI
ECHOCARDIOGRAPHY SEGMENTATION MODEL PERFORMANCE SUMMARY

| Metric Name | Performance |
| --- | --- |
| Dice index | 92 |
| AUC | 97 |

## VI. CONCLUSION AND POSSIBLE FUTURE WORK

In conclusion, it is safe to say that the project was successful. Despite the focus of the project shifting over the course of semester due to data availability issues, the team was able to develop a novel and functioning, useful system. Despite all of the positive moments about the project, there are still a couple of things that can be done.

The system we developed is responsive, fast, reliable, and robust.

Possible future work includes model optimization for high-throughput environments and enabling CI/CD for all models.

### *A. High-throughput optimization*

As of now, models are not developed with load balancing in mind. Dockerizing models and providing more API optimization such as advanced queues, parallel execution, multi-GPU execution, and callbacks are some of the common ways of high-throughput optimization.

The chosen model API framework, FastAPI, supports most of the mentioned functionality, while frameworks such as Torchserve or TensorFlow Serving provide various callbacks multi-GPU solutions.

Advanced queues are helpful for load balancing as the first line of defence against many user queries that might flood the system at nearly the same time. Spacing out operation execution based on custom-defined factors such as priority or timestamp is a common way of balancing system load.

Callbacks could help in discarding samples or operations that are too harsh on resources and do not produce viable results, while parallelizing execution on several GPUs is a dependable way of lowering sample inference speeds.

### *B. CI/CD infrastructure development*

Developing infrastructure for Continuous Integration/Continuous Development for models ensures that the models work and perform correctly at all times. Services such as Weights&Biases and MLFlow can be used for monitoring model performance and hardware load. On top of that, the mentioned systems can be used for automated optimal hyperparameter sweeping and instilling. Online training on new samples is also a possibility with the use of Weights&Biases or MLFlow.

Monitoring model performance is vital for any production machine learning model as it allows engineers to understand if their model is inferencing correctly. Hardware load is usually tracked so that the system does not collapse due to insufficient RAM or VRAM, or is not too slow with data transfer or simple calculations due to high disk or CPU load.

Optimal hyperparameter sweep is essential for production models because it searches for the best hyperparameters for each model, thus ensuring proper performance. Online training on newly provided samples increases robustness of model performance due to exposing the model to new training weights that get captured by the network. By seeing more diverse types of data, the model learns different features that are responsible for correct pattern matching and does not overfit, consequently, it performs more robustly on completely new data.

## REFERENCES


[1] G. Savarese and L. Lund H, "Global public health burden of heart failure," *Cardiac Failure Review*, vol. 3, no. 1, pp. 7–11, 2017.

[2] K. L. Grady, "Management of heart failure in older adults," *Journal of Cardiovascular Nursing*, vol. 21, no. 5, 2006.

[3] P. Ponikowski, S. D. Anker, K. F. AlHabib, M. R. Cowie, T. L. Force, S. Hu, T. Jaarsma, H. Krum, V. Rastogi, L. E. Rohde, U. C. Samal, H. Shimokawa, B. Budi Siswanto, K. Sliwa, and G. Filippatos, "Heart failure: preventing disease and death worldwide," *ESC Heart Failure*, vol. 1, no. 1, pp. 4–25, 2014.

[4] B. Bozkurt, G. C. Fonarow, L. R. Goldberg, M. Guglin, R. A. Josephson, D. E. Forman, G. Lin, J. Lindenfeld, C. O'Connor, G. Panjrath, I. L. Piña, T. Shah, S. S. Sinha, and E. Wolfel, "Cardiac rehabilitation for patients with heart failure: Jacc expert panel," *Journal of the American College of Cardiology*, vol. 77, no. 11, pp. 1454–1469, 2021.

[5] C. Costa, A. Silva, and J. L. Oliveira, *Current Perspectives on PACS and a Cardiology Case Study*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2007, pp. 79–108. [Online]. Available: https://doi.org/10.1007/978-3-540-72375-2$_5$

[6] T. Ben Gal, B. Ben Avraham, D. Milicic, M. G. Crespo-Leiro, A. J. Coats, G. Rosano, P. Seferovic, F. Ruschitzka, M. Metra, S. Anker, G. Filippatos, J. Altenberger, S. Adamopoulos, Y. D. Barac, O. Chioncel, N. de Jonge, J. Elliston, M. Frigerio, E. Goncalvesova, I. Gotsman, A. Grupper, R. Hamdan, Y. Hammer, T. Hasin, L. Hill, O. Itzhaki Ben Zadok, M. Abuhazira, J. Lavee, W. Mullens, S. Nalbantgil, M. F. Piepoli, P. Ponikowski, L. Potena, A. Ristic, A. Ruhparwar, A. Shaul, L. F. Tops, S. Tsui, S. Winnik, T. Jaarsma, and F. Gustafsson, "Guidance on the management of left ventricular assist device (lvad) supported patients for the non-lvad specialist healthcare provider: executive summary," *European Journal of Heart Failure*, vol. 23, no. 10, pp. 1597–1609, 2021.

[7] L. W. Miller, M. Guglin, and J. Rogers, "Cost of ventricular assist devices," *Circulation*, vol. 127, no. 6, pp. 743–748, 2013.

[8] A. Povoroznyuk and A. Filatova, "Development of alternative diagnostic feature system in the cardiology decision support systems," - , no. 3 (9), pp. 39–44, 2016.

[9] M. D. Samad, A. Ulloa, G. J. Wehner, L. Jing, D. Hartzel, C. W. Good, B. A. Williams, C. M. Haggerty, and B. K. Fornwalt, "Predicting survival from large¬†echocardiography and electronic¬†health¬†record datasets," *JACC: Cardiovascular Imaging*, vol. 12, no. 4, pp. 681–689, 2019. [Online]. Available: https://www.jacc.org/doi/abs/10.1016/j.jcmg.2018.04.026

[10] P. J. Bentley, "istethoscope: a demonstration of the use of mobile devices for auscultation," *Mobile Health Technologies: Methods and Protocols*, pp. 293–303, 2015.

[11] D. Ouyang, B. He, A. Ghorbani, N. Yuan, J. Ebinger, C. P. Langlotz, P. A. Heidenreich, R. A. Harrington, D. H. Liang, E. A. Ashley *et al.*, "Video-based ai for beat-to-beat assessment of cardiac function," *Nature*, vol. 580, no. 7802, pp. 252–256, 2020.

[12] M. Meineri, A. E. Van Rensburg, and A. Vegas, "Right ventricular failure after lvad implantation: prevention and treatment," *Best practice & research Clinical anaesthesiology*, vol. 26, no. 2, pp. 217–229, 2012.

[13] S. Shukla, A. Maheshwari, and P. Johri, "Comparative analysis of ml algorithms & stream lit web application," pp. 175–180, 2021.

[14] M. Khorasani, M. Abdou, and J. Hernández Fernández, "Deploying locally and to the cloud," pp. 229–262, 2022.