1 INTRODUCTION

1.1 Overview

Artificial intelligence (AI) is a branch of computing that gives machines the ability to carry out mental tasks similarly to how a human brain would. AI can deliver better results and efficient outcomes with fewer mistakes than human or conventional methods. Deep learning and machine learning teach users to behave or respond in accordance with the facts, producing effective results. For diverse applications of science, several types of AI algorithms (supervised or unsupervised) result in a significant improvement in prediction accuracy. The development of AI and its use in the medical industry has been sparked by the effective storage of patient-related data, analysis, and illness diagnosis. AI algorithms and tools have been successfully created and introduced in the healthcare domain by pioneers from a variety of fields. AI discovers that cardiovascular disease management in particular

1.2 Purpose

According to estimates, 17.9 million people die from cardiovascular diseases (CVDs) each year, which accounts for 31% of all fatalities worldwide.Heart failure is a frequent complication of CVDs, and this dataset contains 9 variables that can be used to estimate heart failure-related mortality.With the aid of a web application and a model leveraging auto AI, we can demonstrate the prediction of heart failure.

2 LITERATURE SURVEY

2.1 Existing problem

The main cause of death worldwide is cardiovascular disease, and these nations bear a disproportionately heavy burden for primary healthcare. In this dissertation, the use of machine learning in the treatment and prevention of cardiovascular disease is examined, as well as the best timing to employ it as the condition progresses[1]. The dissertation discovered that machine learning is applied extremely broadly and in a variety of ways at various phases of the disease, but no stage was determined to be more important than the others. a comprehensive dataset of Chest X-Ray (CXR) pictures was created to aid researchers studying artificial intelligence. 1,083 CXR images were evaluated and commented on by a radiologist as the data were gathered using an eye-tracking device[2]. The dataset includes the following aligned data: eye gaze coordinates, transcribed radiology report text, a CXR image, and radiologist's dictation audio. We anticipate that this dataset can further research in a variety of fields, particularly in the area of multimodal and explicable deep learning/machine learning techniques. These data can also be useful to researchers looking into disease categorization and localization, automated radiology report production, and human-machine interaction. To demonstrate the potential use of this dataset, we provide deep learning experiments that make use of the attention maps generated by the eye gazing dataset.

The datasets from the National Health Insurance Service-Health Screening are used in this study to present a machine learning (ML) algorithm-based prediction model for cardiovascular diseases (CVD). Methods: In order to create the CVD group, we took 4699 individuals who were over 45 and had been given an I20–I25 international classification of illnesses diagnosis. As a separate non-CVD group, 4699 randomly selected subjects were enrolled. Age and gender balance were the same for both groups. The CVD prediction process was carried out using a variety of ML algorithms, and the effectiveness of each prediction model was assessed afterwards[5]. Results: Of all the algorithms validated in this work, extreme gradient boosting, gradient boosting, and random forest showed the best average prediction accuracy (area under receiver operating characteristic curve (AUROC): 0.812, 0.812, and 0.811, respectively). Using AUROC,

Cardiovascular illnesses frequently result in heart failure, which has been the subject of numerous diagnostic techniques. Due to the medical evaluation and the techniques utilised, the failure rate prediction is still unreliable. This study examines the accuracy of an IBM service's machine learning and artificial intelligence-based automatic prediction model for predicting the rate of heart failure[3]. The model is developed after a dataset is trained. The auto AI instance is built in the IBM Watson Studio and connected to machine learning services. "Artificial intelligence enabled patient self-care in chronic heart failure[4]: a paradigm shift from reactive to predictive, preventive, and individualised care," by Matthew Barrett et al. 445–464 in Epma Journal 10.4 (2019).

2.2 Proposed solution

This system's main goal is to use the AutoAI service, which eliminates the need for separate data preprocessing, feature extraction steps, and development, to automate the prediction of heart failure. Data preparation, Model creation, Feature engineering, and Hyper-parameter optimization are all automated using auto AI. You can access the service through IBM Watson Studio. Because of this, skilled data scientists can substantially shorten the experimental period and get started immediately. It offers a multimodal data science and AI environment where experts in data and analytics may work together and improve model performance. Faster selection of the best models and algorithms as well as a speedy start to execution are two advantages of auto AI. Furthermore, it upholds the consistency and integrity of end-to-end AI.

3 THEORITICAL ANALYSIS

3.1 Block diagram

This system's primary goal is to use the AutoAI service to automatically forecast heart failure by performing different data preparation and feature extraction stages. The processing of and development is not required. AI auto automates Feature engineering, model creation, and data preparation Hyper-parameter optimization is another. The service is offered through IBM Watson Studio. Because of this, data scientists swiftly begin and knowledgeable data scientists to accelerate the decrease in experimentation time. Offering a multimodal environment where data and analytics are used in data science and AI Collaboration between professionals and optimization model effectiveness. The advantages of automatic AI are to choose the speed up the best models and algorithms, as well as launch the execution immediately. Additionally, it keeps uniformity and end-to-end consistency AI and ML environment.

The integrated User Interface's automated data preparation and hyper-resolution optimization are its standout features. Finished with parameters Additionally, the deployment is significantly easier where execution occurs in a matter of clicks services. The full lifespan of AI or ML is automated, which is unquestionably a major benefit. AutoAI is analysing the discovers data transformations, algorithms, and parameters alterations Created are these model pipelines iteratively. The planned IBM AutoAI's architecture is depicted in Fig

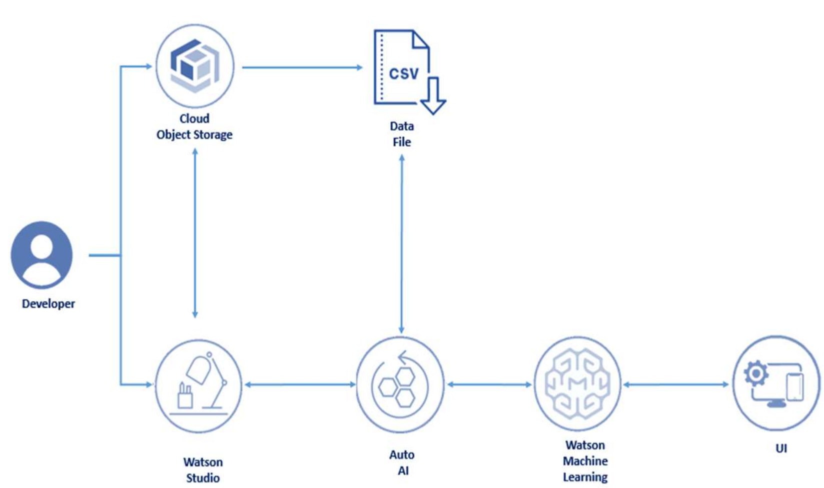

Figure 1. Block Diagram

3.2 Hardware / Software designing

- IBM Watson Studio
- IBM Watson Machine Learning
- Node-RED
- IBM Cloud Object Storage

4 EXPERIMENTAL INVESTIGATIONS

The performance of 4 distinct algorithms is shown in the experiment summary in Fig. 3. The creation of 16 pipelines—4 for each algorithm—can be seen. The infographics in swap view, where all the algorithms are summarised with the pipeline flow and distinct colour schemes for each algorithm, may also be visualised.

Each algorithm pipeline is distinguished by a different colour, and the relevant algorithm's enhancement parameters are represented by the colour black. The progress map and relationship map both show the training process.

Following the procedure, a leaderboard displaying the ranking pipelines is displayed, along with additional outcomes such as a precision-recall curve and confusion matrix. Since it is a binary classification, the prediction has only been based on the two values Y/N. The matrix is displayed after all four parameters—True positive, True negative, False positive, and False negative—have been changed. Gradient Boosting's accuracy value was found to be the best at 0.874. The model is deployed by associating with the machine learning instance in a deployment space. It is examined using test data and results are confirmed.

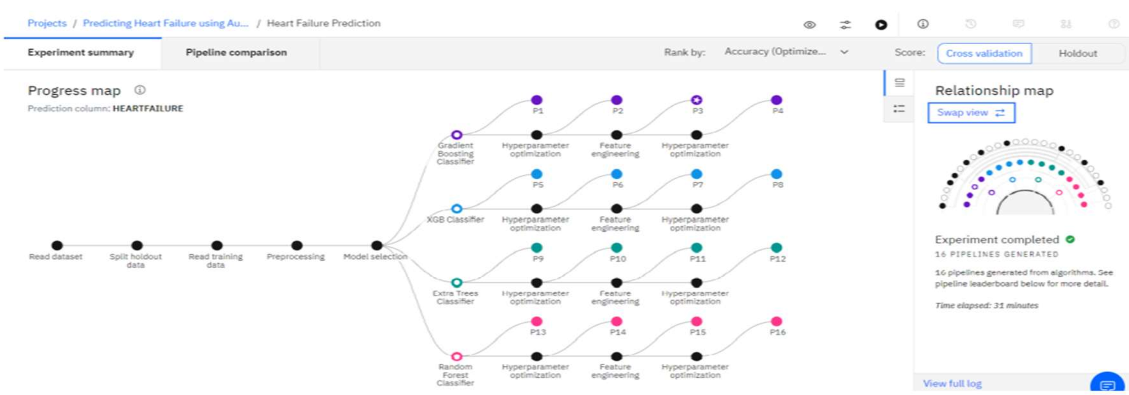

Figure 3. Training the model using Auto AI experiment in association with ML instance

5 FLOWCHART

Figure 2 shows the overall process flow. The services used for the heart failure detection include Node-RED, IBM Cloud Object Storage, IBM Watson Studio, and IBM Watson Machine Learning. Nine variables in the dataset can be utilised to forecast heart failure-related mortality. Using the IBM Auto AI service, a model is created, and a web application is created so that we can obtain the prediction of heart failure. The Asset page in the software option is used to design an AutoAI experiment, which is then carried out. The model is a machine learning model, thus it requires algorithms, metrics, and measures that take that into account. It therefore belongs to the machine learning instance.

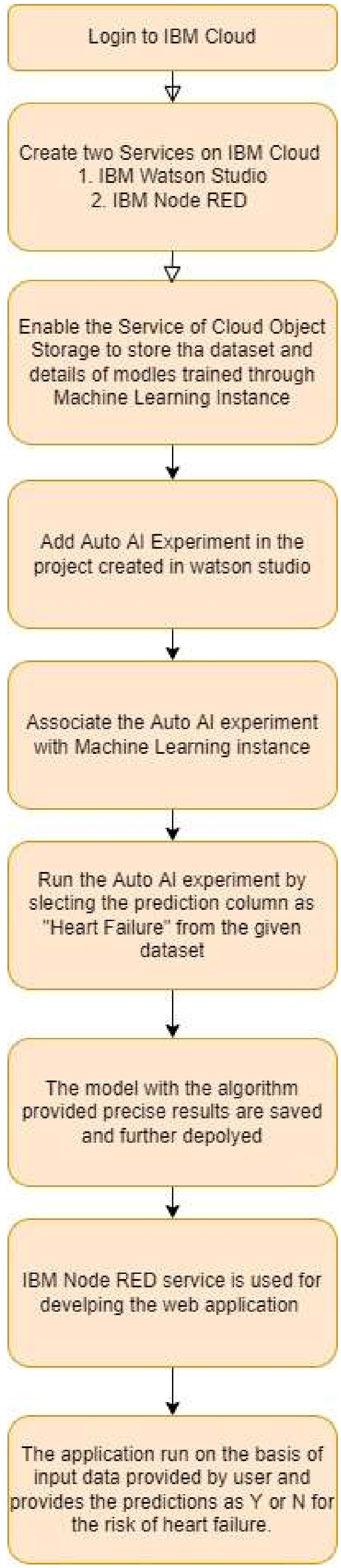

Figure 2. Flow chart of HFPM

6 RESULT

As demonstrated in Fig. 4 , the metric outcomes can also be seen in the model evaluation, and precision and recall measurements.

If the feature is selected differently in the model, the algorithm is immediately changed to reflect this. If palpitations per day is selected, the regression model with RMSE metric is evident. The measure comparison in the pipeline shows all the measures and their accuracy.

The name of the algorithm and further enhancing elements are shown on the dashboard. All 16 pipelines are compared on the pipeline leaderboard, with the parameters algorithm, accuracy, average prediction, F1, Log loss, Precision, Recall, and ROC/AUC values specified.

It is found that, for pipeline 3 with HPO1 and FE enhancement feature, the gradient boosting classifier achieves the highest accuracy of 0.874 in 0.35 minutes.

The fastest method in terms of build time is XGB classifier, which achieves an accuracy of 0.863 in 0.01 seconds without any improvements.

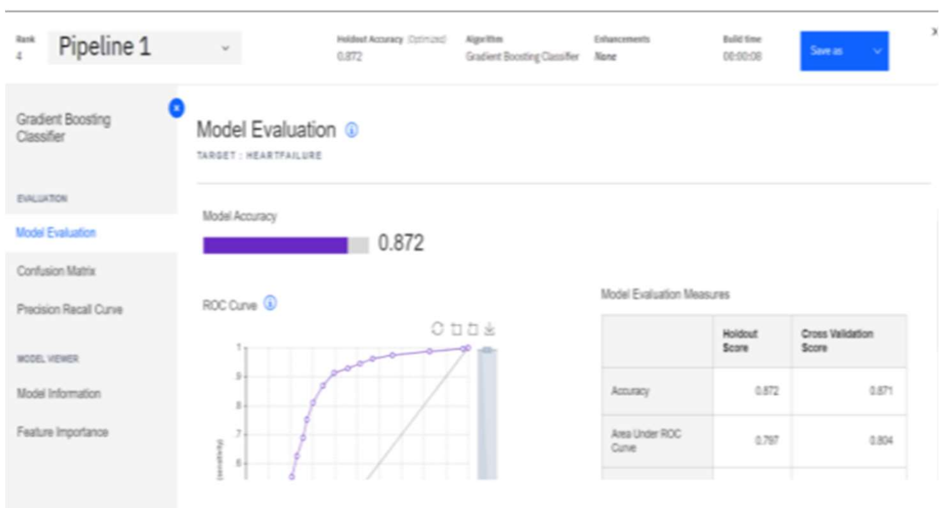

Figure 4. Pipeline 1 Model Evaluation

7 CONCLUSION

One of the most common requirements in the medical industry is the ability to forecast cardiac failure. Here, a Binary classification AutoAI model is effectively implemented without the use of any code thanks to automatically created IBM services. 16 pipelines were run after selecting four algorithms. Accuracy with the Gradient Boosting Algorithm yielded the best performance metric for the model, with a best result of 0.874. The model is deployed with a construction time of

00:00:33 seconds. In order to interface and develop a web service, the model is further evaluated and integrated with the Node Red service. As can be seen, the model correctly predicted the class Y/N indicating the likelihood of heart failure or absence of heart failure. the services provided by the IBM Watson studio, AutoAI, NodeRED, and Cloud services are used, and a model is successfully deployed automatically.

7 ADVANTAGES & DISADVANTAGES

Advantages

1. Developed system is beneficial to patients who are having family history of heart failure
2. Developed system can also be used for monitoring health of patients at health care institutes.
3. Patient can decide the pattern of exercise to be done based on the predictions made.

Disadvantages

1. As the data set includes few samples the predictions made may be wrong for a few patients.

8 APPLICATIONS

The developed system can be used by hospitals and clinics to monitor the health of the patients. Also mobile application can be developed for the system so that patients can monitor their health and keep track of the same.

9 FUTURE SCOPE

Additionally, the developed model can be utilized to raise public awareness of heart failure. Therefore, an application can be made to be a preventive measure for failures rather than one for failure detection.

A real-time mobile application can be constructed using a variety of other IBM services. The automatic and quick development of chatbots, natural language disambiguation, and sensor-based cloud applications is also possible.

10 BIBILOGRAPHY

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[7] Dataset source: https://github.com/IBM/predictive-model-on-watsonml/blob/master/data/patientdataV6.csv

APPENDIX

A. Source Code

Attach the code for the solution built.