



Diabetes prediction of a patient by *Group 06*

Enrico Maria Di Mauro
Allegra Cuzzocrea

0622701706
0622701707

e.dimauro5@studenti.unisa.it
a.cuzzocrea2@studenti.unisa.it



Summary

1.	Introduction	1
2.	Software	2
3.	Pipeline	3
3.1.	Arrikto Deployment	3
3.2.	Kubeflow Notebook	3
3.3.	Kubeflow Pipeline	4
3.3.1.	Prerequisites	4
3.3.2.	Components	5
3.3.2.1.	save_file	5
3.3.2.2.	clarke_error_grid	5
3.3.2.3.	data_history	6
3.3.2.4.	epochs_loss	6
3.3.2.5.	real_pred	6
3.3.2.6.	get_ids_csvs	7
3.3.2.7.	load_data	7
3.3.2.8.	split_data	7
3.3.2.9.	build_model	8
3.3.2.10.	train_model	8
3.3.2.11.	test_model	8
3.3.2.12.	model_manipulation	9
3.3.2.13.	metrics_evaluation	9
3.3.2.14.	main	10
3.3.3.	Graph	11
3.3.4.	Katib	11
3.4.	Further information	13
4.	Web App	14
4.1.	Creation	14
4.1.1.	Streamlit	14
4.2.	Deployment	16
4.2.1.	Docker	16
4.2.2.	Kubernetes	19
4.3.	Further information	26
5.	Security	27

1. Introduction

The aim of the project is the exploration, training and serving of a machine learning model for Time Series Data forecasting by leveraging Kubeflow's main components.

The Time Series Data forecasting task consists in **predicting accurate blood glucose levels in Type 1 Diabetes patients**. Blood glucose level prediction is a challenging task for AI researchers, with the potential to improve the health and wellbeing of people with diabetes. Knowing in advance when blood glucose is approaching unsafe levels provides time to pro-actively avoid hypo- and hyperglycaemia and their concomitant complications. The drive to perfect an artificial pancreas has increased the interest in using machine learning approaches to improve prediction accuracy.

The problem to be solved is a time-series regression problem represented by the glucose levels in future instants of times, i.e., horizon $h\Delta(t)$.

This regression is affected by considering available the glucose level $G(t)$, the injected insulin $I(t)$ and the carbohydrates intake $C(t)$ in a time window of $k\Delta(t)$ before the current instant t .

The time series prediction task is transformed in the following **regression problem**:

$$\hat{G}(t + h\Delta(t)) = f(G(t), G(t - \Delta(t)), \dots, G(t - k\Delta(t)), I(t), I(t - \Delta(t)), \dots, I(t - k\Delta(t)), C(t), C(t - \Delta(t)), \dots, C(t - k\Delta(t)))$$

In this way having past values of glucose, insulin and carbohydrates it is possible to predict next glucose levels.

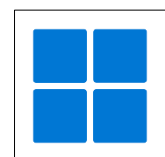
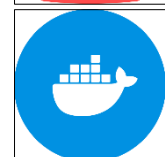
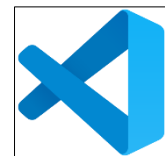
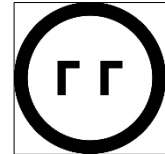
The **primary goals** of the project are:

- **Design a Kubeflow Pipeline** that creates a patient personalized ML prediction model using its recorded data
- **Design and deploy a Web App** that exploits the patient model and makes the glucose prediction to determine if there is the risk of a diabetes complication

2. Software

- **Kubeflow** and **Arrikto**: Kubeflow is an open-source platform for machine learning on Kubernetes, which simplifies the deployment of machine learning workflows. Kubeflow includes tools for model development (Kubeflow Notebooks), training and validation (Kubeflow Pipelines), monitoring and management (Kubeflow Dashboard) and automated machine learning (Katib). Arrikto offers a managed Kubeflow service called the **Arrikto Managed Kubeflow (AMK)**, which provides a fully managed and highly available Kubeflow environment. AMK makes it easy to use Kubeflow by abstracting away the complexity of deploying and managing Kubeflow on Kubernetes. Kubeflow and Arrikto can be used together to provide a powerful and flexible platform for building, training and deploying machine learning models. AMK makes it easy to deploy and manage Kubeflow on Kubernetes, while Kubeflow provides the tools and infrastructure needed to build, train and serve machine learning models at scale
- **Visual Studio Code**: it is a free, open-source code editor that supports multiple programming languages. It's a popular choice among developers due to its versatility and extensibility through the use of plugins and extensions
- **Streamlit**: it is an open-source Python library that allows developers to create interactive web applications for machine learning and data science quickly and easily with only a few lines of code
- **Docker**: it is a software platform that allows developers to package and deploy applications as portable containers. It provides a standardized way to build and distribute applications, making it easier to deploy and run them consistently across different computing environments. Docker containers are self-contained and include everything needed to run the application. This makes it easier to build and deploy applications in a consistent and reliable way and reduces the risk of compatibility issues between different computing environments
- **Kubernetes**: it is an open-source container orchestration platform that automates the deployment, scaling and management of containerized applications. It provides a way to manage and orchestrate containers across multiple hosts, making it easier to deploy and run applications in a scalable and fault-tolerant manner. Kubernetes uses a declarative configuration to define the desired state of the application and continuously monitors the actual state to ensure that it matches the desired state. It can automatically scale the application up or down based on resource utilization and can also handle failover and self-healing of the application in case of node failures or other issues. It supports a wide range of container runtimes, including Docker and provides a rich set of features such as load balancing, service discovery and rolling updates for container-based applications

Note that everything was tested on both Operating Systems **Windows** and **Linux**. For the second one it was used **Windows Subsystem for Linux (WSL)** that is a Windows feature that permits to run Linux commands and applications natively on a Windows system without the need for a virtual machine or dual-boot setup

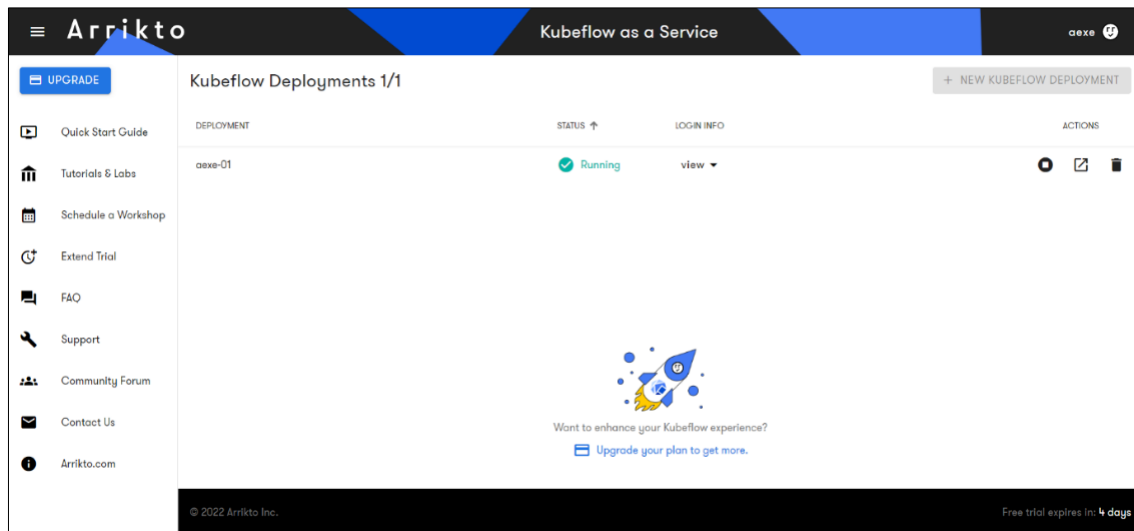


3. Pipeline

This section aims to present all steps that led to the generation of the Pipeline. In particular, the service **Arrikto Managed Kubeflow** was used to create the Pipeline and so to build, train and validate the patients personalized models.

3.1. Arrikto Deployment

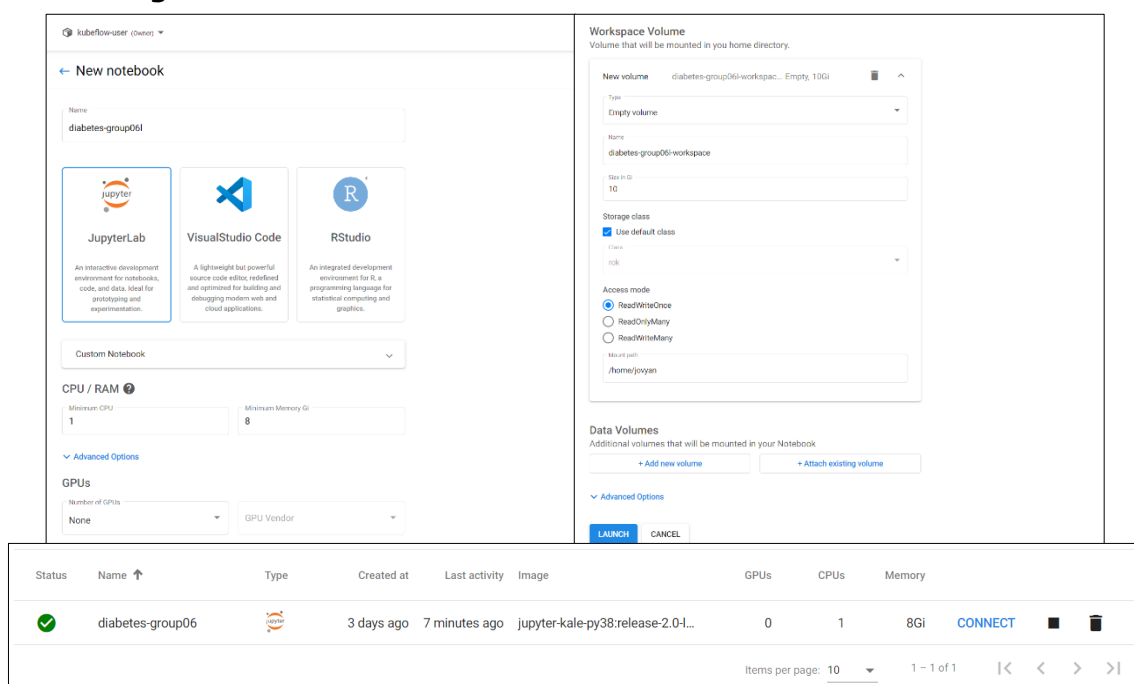
The **registration** to Arrikto permitted to create a deployment. This took about 40 minutes.



3.2. Kubeflow Notebook

After the deployment configuration a **Jupyter Notebook** was created with the following setup:

- **CPU:** 1
- **RAM:** 8 GB
- **Storage:** 10 GB



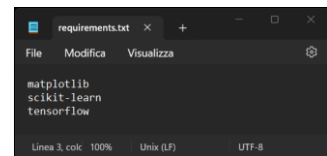
3.3. Kubeflow Pipeline

3.3.1. Prerequisites

The file `'requirements.txt'` is provided in order to install all necessary packages for the Pipeline. Before installing them, it is advisable to upgrade the pip package. It is possible to run the following commands:

```
!pip install --upgrade pip
```

```
!pip install --user -r requirements.txt
```



- Upgrade pip, then restart the kernel and run again (the warning will disappear)

```
!pip install --upgrade pip
```

Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: pip in /home/jovyan/.local/lib/python3.8/site-packages (23.0.1)

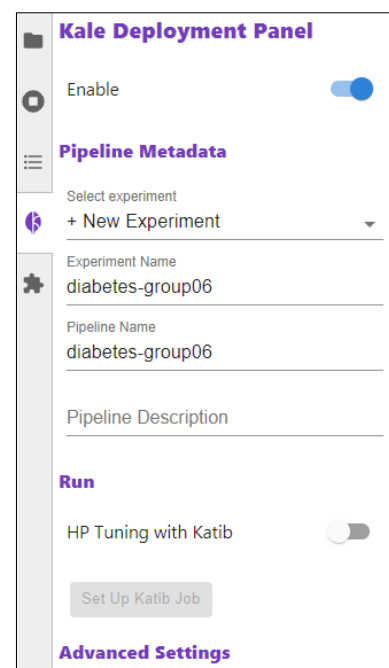
- Install requirements, then restart the kernel again (dependencies warnings can be ignored)

```
!pip install --user -r requirements.txt
```

Another prerequisite is enabling the **Kale Deployment Panel**. In fact, Kale is a tool that permits to create a Kubeflow Pipeline from a Jupyter Notebook. In particular, it is possible to annotate the cells of the Notebook selecting from 6 Kale cell types. The annotations are used by Kale to define the Pipeline, specifically to manage dependencies and marshal data correctly as inputs and outputs for each step.

Below it is shown the list and a brief summary of **cell types**.

Cell type	Cell should contain
Imports	Blocks of code that import other modules your machine learning pipeline requires and may be needed by more than one step.
Functions	Functions used later in your machine learning pipeline; global variable definitions (other than pipeline parameters); and code that initializes lists, dictionaries, objects, and other values used throughout your pipeline.
Pipeline Parameters	Definitions for global variables used to parameterize your machine learning workflow. These are often training hyperparameters.
Pipeline Metrics	Lines of code that log or print values used to measure the success of your model.
Pipeline Step	Code that implements the core logic of a discrete step in your workflow.
Skip Cell	Any code that you want Kale to ignore.



The **imports** in the Notebook are the following ones:

```
from matplotlib import pyplot as plt
from numpy import concatenate, save
from numpy.random import seed
from os import environ, makedirs, path, scandir
environ['TF_CPP_MIN_LOG_LEVEL'] = '2'
from pandas import DataFrame, read_csv
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_absolute_error, mean_squared_error
from tensorflow import keras
from tensorflow.random import set_seed
```

3.3.2. Components

In this section all Pipeline components are reported and the role of each of them is explained.

3.3.2.1. save_file

```
functions
...
This function creates the path in which to save a plot (plots are shown), a numpy array or a model and saves that file
...
def save_file(dir_path, file_name, file = None):
```

This function is useful because it permits to save all kinds of file used. In particular, it saves plots, numpy arrays and models.

It takes in input:

- `dir_path`: path where to save the file. If it does not exist, the function creates it
- `file_name`: name of the file to save
- `file`: optional parameter. If it is not specified, the function saves a plot otherwise it saves the file using the appropriate method based on the extension

3.3.2.2. clarke_error_grid

```
functions
...
This function takes in input the reference values and the prediction values as lists, returns a list with each index corresponding to the total number of points within that zone (0=A, 1=B, 2=C, 3=D, 4=E) and creates the plot of clarke_error_grid
...
def clarke_error_grid(ref_values, pred_values, title_string):
```

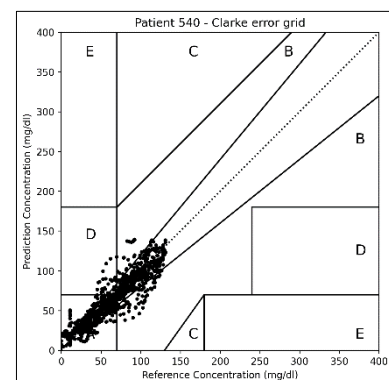
This function generates an image representing the **Clarke Error Grid**.

It takes in input:

- `ref_values`: list containing actual values
- `pred_values`: list containing predicted values
- `title_string`: string containing the title of the image

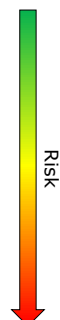
The Clark Error Grid is a useful tool for evaluating the accuracy of glucose monitoring systems and for identifying any issues or errors in monitoring. However, it does not provide information on the degree of glucose control over time or the patient's ability to manage their own glucose.

The Clark Error Grid divides the glucose graph into 5 zones, representing the combination of glucose values measured by the monitoring system and those measured in the laboratory. The zones represent the degree of discrepancy between the 2 measurements and the associated risk of clinical error.



The 5 zones are:

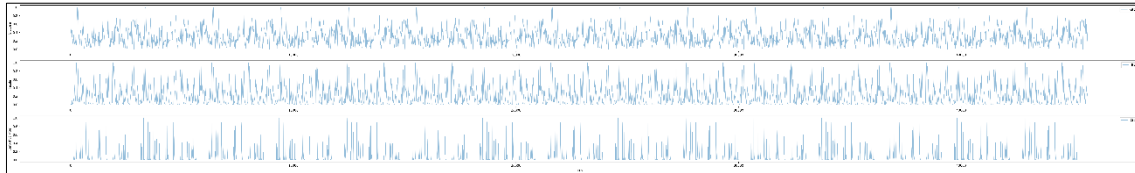
- **Zone A**: prediction values within 20% of the actual values
- **Zone B**: predictions outside 20% of the actual values but not leading to inappropriate treatments
- **Zone C**: predicted values leading to unnecessary treatments
- **Zone D**: prediction points indicating a potential dangerous failure to detect hypoglycaemia or hyperglycaemia
- **Zone E**: prediction values that would confuse the treatment of hypoglycaemia with hyperglycaemia and vice versa



3.3.2.3. data_history

```
functions
'''
This function creates the data history of a patient (glucose, insulin, carbohydrates) and a plot of that history
'''
def data_history(dataset, title_string):
```

This function creates the data history of a patient based on the input dataset. The obtained data history is represented by a plot which has time on the x-axis and glucose, insulin and carbohydrates on the y-axis.



The function takes in input:

- dataset: patient's data
- title_string: string containing the title of the plot

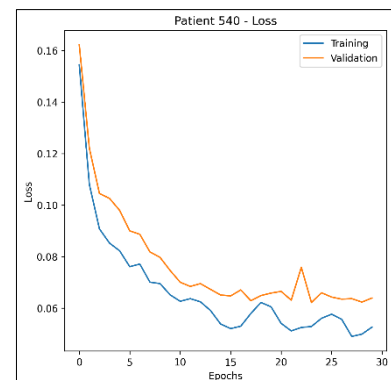
3.3.2.4. epochs_loss

```
functions
'''
This function creates the plot of training loss and validation loss of a model
'''
def epochs_loss(history, title_string):
```

This function creates a plot which compares the training loss and the validation loss of a model. In particular, the plot has the number of epochs on the x-axis and the training and validation loss on the y-axis.

The function takes in input:

- history: output of fit method
- title_string: string containing the title of the plot



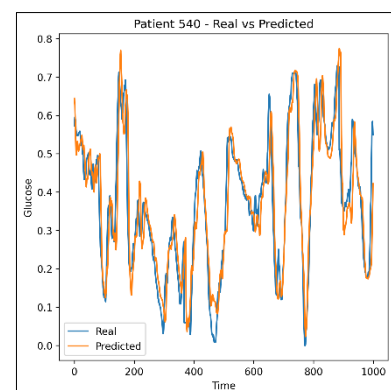
3.3.2.5. real_pred

```
functions
'''
This function creates the plot of real values vs predicted values
'''
def real_pred(real, predicted, title_string):
```

This function creates a plot which compares real values and predicted values. In particular, the plot has time on the x-axis and glucose on the y-axis.

The function takes in input:

- real: list containing real values
- predicted: list containing predicted values
- title_string: string containing the title of the plot



3.3.2.6. get_ids_csvs

```
step: get_ids_csvs
'''
This function takes in input a directory containing all patients and creates a dictionary containing the associations id - csv of the patients,
saves a numpy array containing ids of the patients and returns the dictionary
'''
def get_ids_csvs(dir_path):
```

This function is useful to extract the data of interest from the entire dataset. In particular, it creates a dictionary consisting of the associations ids-csvs of the patients and saves a NumPy array containing ids of the patients in '.npy' format.

It takes in input:

- dir_path: path of the directory containing all patients

It returns:

- ids_csvs: dictionary consisting of associations ids-csvs of the patients

3.3.2.7. load_data

```
step: load_data
'''
This function takes in input the csv of a patient in order to load the data, normalizes the latter and returns the final dataset
'''
def load_data(file_csv, patient_id):
```

This function loads the data of a patient, normalizes them and provides the final dataset.

It takes in input:

- file_csv: csv of a patient
- patient_id: id of the patient

it returns:

- final_dataset: final dataset of the patient

3.3.2.8. split_data

```
step: split_data
'''
This function splits a dataset. In this case, it is used to obtain training and test sets (the validation set will be obtained
using the 'validation_split' parameter of the fit function on the train set in the train_data function)
'''
def split_data(dataset, test_size, patient_id):
```

This function splits a dataset in Training set and Test set. The Validation set will be obtained using the 'validation_split' parameter of the fit function on the Training set used in the train_data function. Furthermore, the function saves the data of the obtained Test set and the associated labels as NumPy arrays in '.npy' format because these files will be useful in Web App phase.

The function takes in input:

- dataset: data of the patient
- test_size: desired size of the Test set
- patient_id: id of the patient

It returns:

- train_X: data of the obtained Training set
- train_y: labels of the Training set
- test_X: data of the obtained Test set
- test_y: labels of the testing set

3.3.2.9. build_model

```
step: build_model
...
This function designs and builds a LSTM model using a LSTM layer and 2 Dense layers, MAE as loss metric and Adam as optimizer
...
def build_model(units, input1, input2):
```

This function designs and builds a **LSTM model**. The created model consists of a LSTM layer and 2 Dense layers. Therefore, Mean Absolute Error (MAE) was used as loss metric and Adam as optimizer.

The function takes in input:

- units: neurons number of the LSTM layer
- input1: timesteps number
- input2: features number

3.3.2.10. train_model

```
step: train_model
...
This function trains and saves the LSTM model
...
def train_model(train_X, train_y, model, epochs, batch_size, patient_id):
```

This function trains the LSTM model and saves it.

It takes in input:

- train_X: data of the obtained Training set
- train_y: labels of the Training set
- model: trained model to us for the training
- epochs: number of epochs for the training
- batch_size: batch size for the training
- patient_id: id of the patient

3.3.2.11. test_model

```
step: test_model
...
This function tests the LSTM model on the test set, plotting the prediction and the real values and plotting the clarke error grid
...
def test_model(test_X, test_y, model, patient_id):
```

This function tests the LSTM model on the Test set, plotting the comparison between the real values and the predicted ones. Furthermore, it plots the Clarke Error Grid.

The function takes in input:

- test_X: data of the Test set
- test_y: labes of the Test set
- model: model used for the testing
- patient_id: id of the patient

It returns:

- inv_y: actual values
- inv_yhat: predicted values

3.3.2.12. model_manipulation

```
step: model_manipulation depends on: ● ● ● ●
'''
This function creates, trains and tests a model for each patient of the patients list
'''
def model_manipulation(dataset, patient_id):
```

This function creates, trins and tests a model for each patient of the patients list.

It takes in input:

- dataset: dataset of the patient of interest
- patient_id: id of the patient

It returns:

- real: actual values
- predicted: predicted values

This component has the following dependencies:

- split_data
- build_model
- train_model
- test_model

3.3.2.13. metrics_evaluation

```
step: metrics_evaluation
'''
This function takes in input the real value and the predicted value in order to calculate the evaluation metrics (MAE, MSE, RMSE)
'''
def metrics_evaluation(real, predicted):
```

This function calculates the evaluation metrics MAE, MSE and RMSE. In particular:

- **MAE**: Mean Absolute Error $MAE = \sum_{i=1}^n \frac{|\hat{y}_i - y_i|}{n}$
- **MSE**: Mean Squared Error $MSE = \sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{n}$
- **RMSE**: Root Mean Squared Error $RMSE = \sqrt{\sum_{i=1}^n \frac{(\hat{y}_i - y_i)^2}{n}}$

Note that this function permits to calculate 3 types of evaluation metrics but in the next steps **only MAE will be used**.

It takes in input:

- real: actual values
- predicted: predicted values

It returns:

- mae: calculated Mean Squared Error
- mse: calculated Mean Absolute Error
- rmse: calculated Root Meand Squared Error

3.3.2.14. main

```
step: main depends on: ●●●●●
'''
This is the main function that starts the pipeline
'''
def main():
    seed(819)
    set_seed(819)

    initial_path = 'Datasets'
    ids_csvs = get_ids_csvs(initial_path)

    # Obtain the mae for each patient of the ids_csvs dictionary (executing the pipeline for each patient)
    for patient in sorted(ids_csvs):
        print('-----\n\t\t\t\t\tPatient {patient}\n-----')

        dataset = load_data(f'{initial_path}/{patient}/{ids_csvs[patient]}', patient)
        real, predicted = model_manipulation(dataset, patient)
        mae, mse, rmse = metrics_evaluation(real, predicted)
        globals()[f'mae{patient}'] = mae # for the pipeline_metrics we use only the mae

if __name__ == '__main__':
    main()
```

This function is the general function that calls the other ones to generate a trained model for each patient of the patients list and to calculate the evaluation metrics.

This component has the following dependencies:

- get_ids_csvs
- load_data
- model_manipulation
- metrics_evaluation

3.3.3. Graph

The Pipeline is a **Directed Acyclic Graph (DAG)**. In particular, each node of the graph is a component and a Docker container.

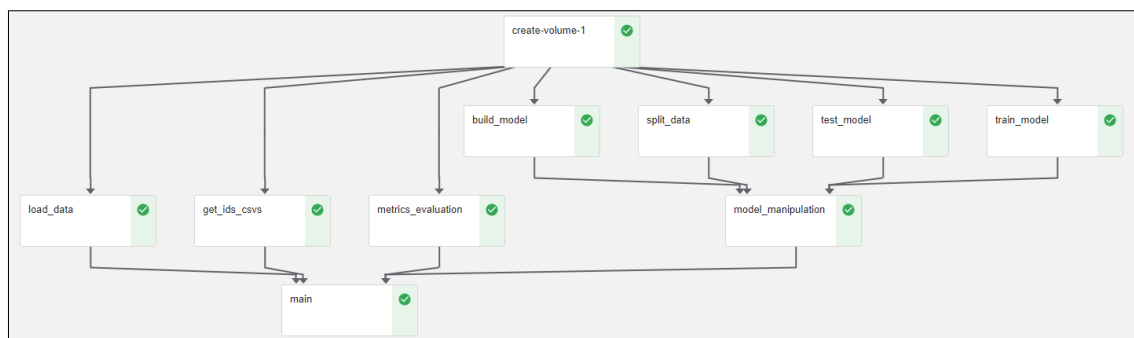
The Pipeline blocks in KubeFlow are the functional components that make up the Machine Learning workflow. Each block performs a specific operation.

The Pipeline blocks are executed as Docker containers on Kubernetes. This means that each Pipeline block is packaged in a Docker image that contains the application, dependency libraries, configuration data, and so on.

The fact that Pipeline blocks are executed as Docker containers on Kubernetes offers numerous advantages. Firstly, it permits the isolation of the execution environment of each block, ensuring that the dependencies and libraries used by one block do not interfere with those of other blocks. Secondly, it enables the entire Pipeline process to be reproducible, as each block is executed in a uniform and predictable environment.

In conclusion, the use of Docker containers on Kubernetes makes KubeFlow Pipeline blocks isolated, reproducible, and scalable, facilitating the management of the entire Machine Learning workflow.

Below it is shown the obtained Pipeline.



3.3.4. Katib

Katib is a KubeFlow component which allows for the **Automated Hyperparameters Tuning**. In a previous section Kale was introduced as a tool to define a Pipeline and it was said that it is necessary to enable the Kale Deployment Panel.

To enable Katib it is necessary to enable the **HP Tuning with Katib** too.

Furthermore, the following cells must be added in the Jupyter Notebook:

- **Pipeline-parameters:** it contains the editable parameters. This cell is located after the Imports cell within the Notebook
- **Pipeline-metrics:** it contains the metrics which have to be optimized by varying the parameters contained in the Pipeline-parameters cell

```
pipeline-parameters
units = 60
epochs = 30
batch_size = 128
```

```
pipeline-metrics
print(mae540)
print(mae544)
print(mae552)
print(mae559)
print(mae563)
print(mae567)
```

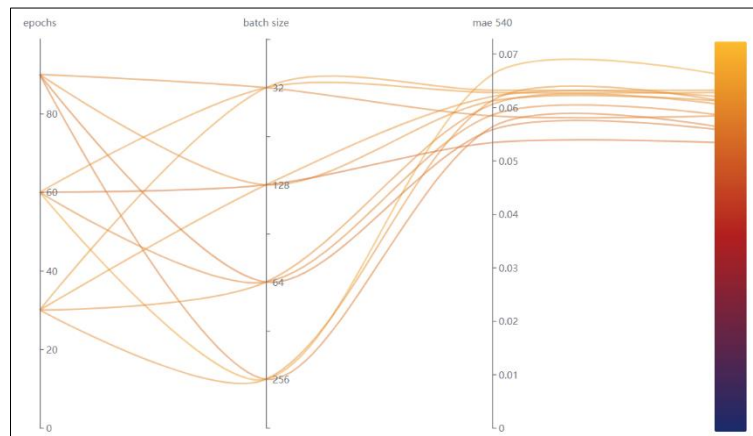
To configure Katib it is possible to click on **Set Up Katib Job**.

Below it is explained the utility of each section in Katib Job configuration.

- **Search Space Parameters:** it permits to specify the parameters which can be edited during the execution. It is possible to choose specific values or a range. In the figure it is possible to see that the number of epochs vary from 30 to 90 with a step of 30 and the values for the batch size are 32, 64, 128, 256. Furthermore, because of the excessive quantity of time required units was excluded
- **Search Algorithm:** it permits to specify the algorithm to optimize the metrics. As it is possible to see in the figure, Random Search was selected
- **Search Objective:** it permits to specify a metric to optimize and the optimization way (minimization or maximization). Only one metric at a time can be optimized. As it is possible to see in the figure, MAE for a patient at a time was selected
- **Run Parameters:** it permits to specify the number of parallel trials, the maximum number of trials and the maximum number of failed trials. Exceeding the second or the third one the execution ends. As it is possible to see in the figure, the number of parallel trials was set to 3, the maximum number of trials was set to 200 and the maximum number of failed trials was set to 12

Finally, to run the Pipeline using the Automated Hyperparameters Tuning it is possible to click on **Compile and Run Katib Job**.

Below it is shown the final result.



As it is possible to see in the figure, the best values configuration for epochs and batch size is:

- **Epochs:** 60
- **Batch size:** 128

This configuration permits to obtain a MAE for patient with id 540 of approximately equal to 0.05.

Doing the same thing for each patient, it was obtained that MAE assumes similar values for all patients.

3.4. Further information

For the correct functioning of the Pipeline and so to create a model for a patient, it is necessary to have the corresponding dataset. In particular, in datasets directory there has to be a subdirectory named with the patient id containing a csv file named 'patient_id-ws-testing(t+30).csv'.

Note that each created file is saved in 'Patients_info/patient_id' in order to simplify the future loadings.

The '**pipeline**' directory of the project is characterized by the structure represented alongside.

```
C:\.
├── diabetes-group06-n29e7.katib.yaml
├── diabetes-group06-n29e7.yaml
├── Diabetes_Group06.ipynb
├── requirements.txt
├── Datasets
│   ├── 540
│   │   ├── 540-ws-testing(t+30).csv
│   │   └── 540-ws-testing(t+30).png
│   ├── 544
│   │   ├── 544-ws-testing(t+30).csv
│   │   └── 544-ws-testing(t+30).png
│   ├── 552
│   │   ├── 552-ws-testing(t+30).csv
│   │   └── 552-ws-testing(t+30).png
│   ├── 559
│   │   ├── 559-ws-testing(t+30).csv
│   │   └── 559-ws-testing(t+30).png
│   ├── 563
│   │   ├── 563-ws-testing(t+30).csv
│   │   └── 563-ws-testing(t+30).png
│   └── 567
│       ├── 567-ws-testing(t+30).csv
│       └── 567-ws-testing(t+30).png
├── Patients_info
│   ├── patients.npy
│   ├── 540
│   │   ├── 540_clarke.png
│   │   ├── 540_data_history.png
│   │   ├── 540_loss.png
│   │   ├── 540_model.h5
│   │   ├── 540_real_pred.png
│   │   ├── 540_test_X.npy
│   │   └── 540_test_y.npy
│   ├── 544
│   │   ├── 544_clarke.png
│   │   ├── 544_data_history.png
│   │   ├── 544_loss.png
│   │   ├── 544_model.h5
│   │   ├── 544_real_pred.png
│   │   ├── 544_test_X.npy
│   │   └── 544_test_y.npy
│   ├── 552
│   │   ├── 552_clarke.png
│   │   ├── 552_data_history.png
│   │   ├── 552_loss.png
│   │   ├── 552_model.h5
│   │   ├── 552_real_pred.png
│   │   ├── 552_test_X.npy
│   │   └── 552_test_y.npy
│   ├── 559
│   │   ├── 559_clarke.png
│   │   ├── 559_data_history.png
│   │   ├── 559_loss.png
│   │   ├── 559_model.h5
│   │   ├── 559_real_pred.png
│   │   ├── 559_test_X.npy
│   │   └── 559_test_y.npy
│   ├── 563
│   │   ├── 563_clarke.png
│   │   ├── 563_data_history.png
│   │   ├── 563_loss.png
│   │   ├── 563_model.h5
│   │   ├── 563_real_pred.png
│   │   ├── 563_test_X.npy
│   │   └── 563_test_y.npy
│   └── 567
│       ├── 567_clarke.png
│       ├── 567_data_history.png
│       ├── 567_loss.png
│       ├── 567_model.h5
│       ├── 567_real_pred.png
│       ├── 567_test_X.npy
│       └── 567_test_y.npy
```

4. Web App

This section aims to present all steps that led to the realization of the Web App able to perform the prevision.

4.1. Creation

This section describes the process of creation and testing of the Web App.

In particular, the open-source Python library **Streamlit** was used.

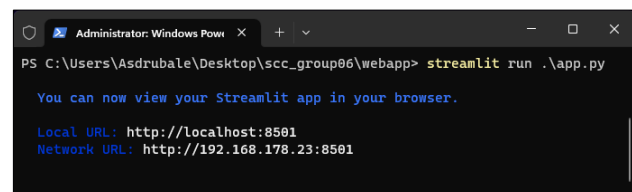
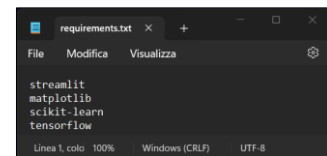
4.1.1. Streamlit

After writing the code, to launch the App it is necessary to place in the webapp directory, install the requirements present in the provided **'requirements.txt'** file by running the following command:

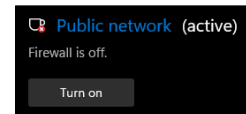
```
pip install -r requirements.txt
```

At this point it is possible to run the **'app.py'** file by using the following command:

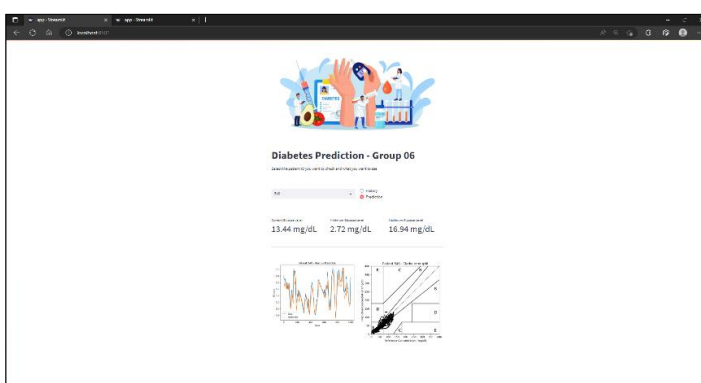
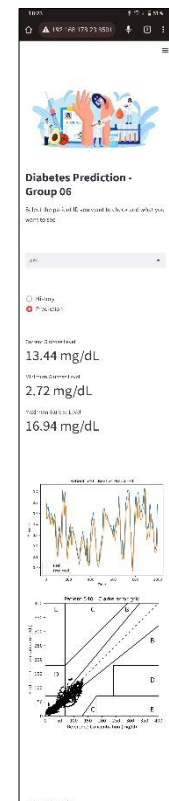
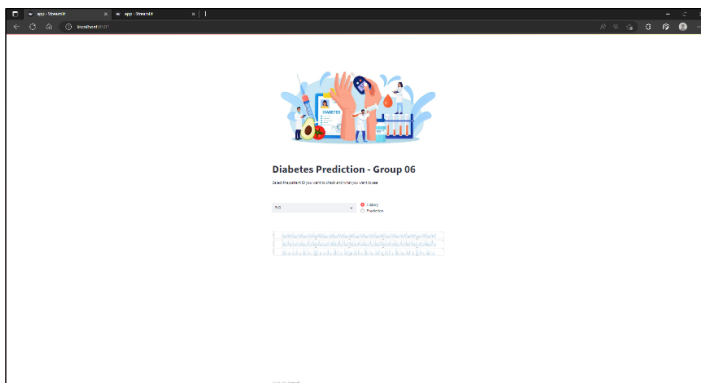
```
streamlit run app.py
```



After running this command any device present in the same network can access the app using the second URL which represents the IP Address of the machine which the command is run on. To do this, if the command above is run on Windows it is necessary to **deactivate the Firewall**.



The Web App visualizations on a computer and on a smartphone are the following ones:



Thanks to the selection box it is possible to select a patient. Selectable patients are those of which it is known a dataset. The list of patients is obtained by loading the **'patients.npy'** file previously created by the Pipeline.

540	<input checked="" type="radio"/> History <input type="radio"/> Prediction
540	<input type="radio"/> History <input checked="" type="radio"/> Prediction

540

540

544

552

559

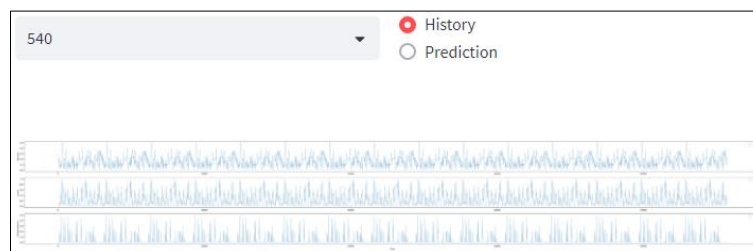
563

567

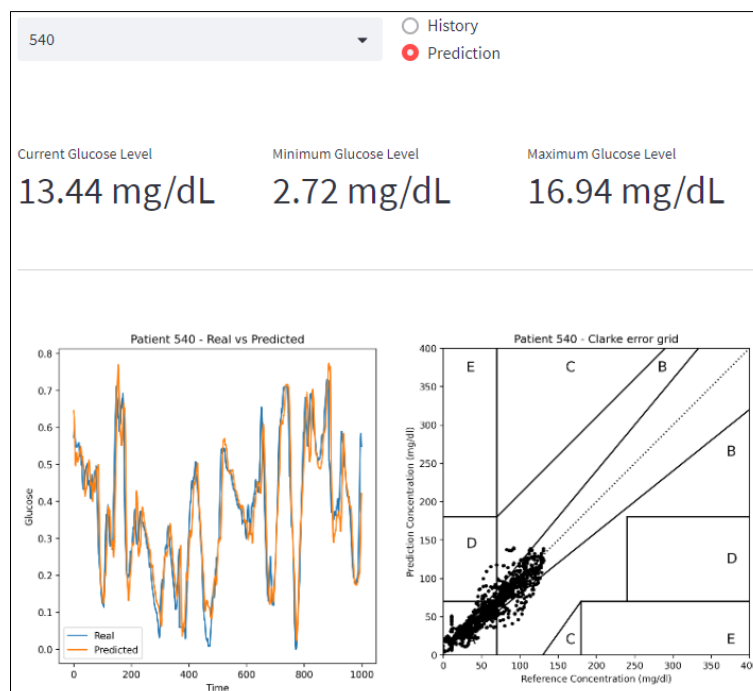
Once selected a patient it is possible to specify what to show thanks to a radio button.

In particular, the 2 possibilities are:

- **History:** the patient data trend over time is shown. Data are represented by glucose, insulin and carbohydrates values. The image containing the plot is obtained by loading the **'data_history.png'** image previously created by the Pipeline



- **Prediction:** current, minimum and maximum glucose predicted values are calculated and shown after reading the patient csv. In addition to these, there are 2 plots which represent the comparison between real and predicted values and the Clark Error Grid. To do this the appropriate patient **'test_X.npy'**, **'test_y.npy'** and model previously created by the Pipeline are loaded. Then the **'test_model.h5'** function makes the prediction and saves the plots.



4.2. Deployment

This section describes the Web App deployment process.

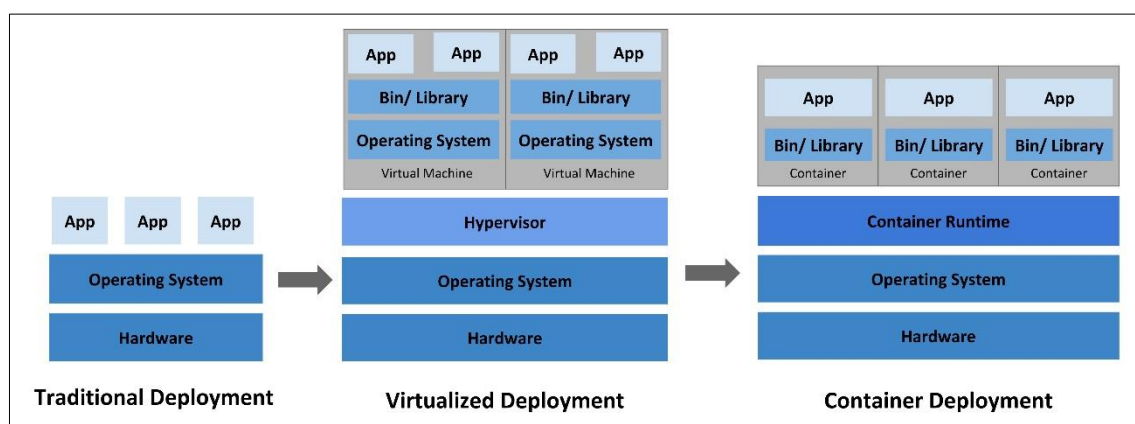
Deployment is the process of transferring a web application from the development server to the production server, so that it can be accessed by its end users on the Internet. In other words, deployment is the process of 'putting into production' the web application, so that it can be run on a server and made available to its users. Deployment is a critical part of the web application lifecycle, as an incorrect deployment can cause security, performance, reliability, and availability issues for the application.

In particular, **Docker** and **Kubernetes** were used.

4.2.1. Docker

Docker is a containerization technology that allows developers to package an application, configurations and all its dependencies into a single container. Using Docker simplifies the Web App deployment process. In particular, it offers several advantages:

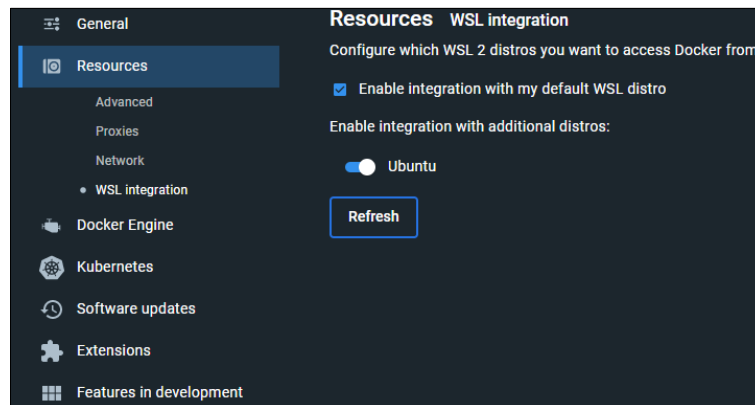
- **Portability:** Docker containers can be run on any system that supports Docker, regardless of the underlying operating system. This means that you can develop and test your app on one machine, and then deploy it on another without worrying about compatibility issues
- **Consistency:** Docker ensures that your app is deployed with the same configuration and dependencies every time, which reduces the risk of issues caused by differences in environments
- **Scalability:** Docker makes it easy to scale your app horizontally by spinning up additional containers as needed. This allows you to handle spikes in traffic or scale your app to meet changing demands
- **Isolation:** Docker containers provide a level of isolation that helps prevent conflicts between applications or dependencies. This means that you can run multiple applications on the same server without worrying about them interfering with each other
- **Versioning:** Docker allows you to easily manage and deploy different versions of your application, making it easy to roll back to a previous version if needed
- **Efficiency:** Docker containers are lightweight and consume minimal resources, which allows you to run more applications on the same server than you could with traditional virtual machines



A Docker container image is a lightweight, standalone, executable package of software that includes everything needed to run an application: code, runtime, system tools, system libraries and settings.

Docker Desktop was installed.

Since everything was tested both on Windows and WSL, it was necessary for the second one to **enable WSL integration**.



To create a Docker image it was necessary to create a **dockerfile** in the Web App folder.

A dockerfile is a text file that contains a series of instructions that Docker uses to build a Docker image. The dockerfile provides a recipe for building a container image that includes all the necessary dependencies, configuration, and code needed to run a specific application

```
webapp > dockerfile > ...
1  FROM python
2
3  WORKDIR /diabetes-group06
4
5  COPY . .
6
7  WORKDIR /diabetes-group06/webapp
8
9  RUN apt-get update && apt-get install -y
10 RUN pip install --upgrade pip && pip install -r requirements.txt
11
12 EXPOSE 8501
13
14 ENTRYPOINT ["streamlit", "run", "app.py", "--server.port=8501", "--server.address=0.0.0.0"]
```

Below it is described the functionality of each part of the dockerfile:

- **FROM:** it specifies the base image to use for this Docker image. In this case, the base image is Python, which means that Python is already installed in the Docker image
- **WORKDIR:** it sets the working directory for the subsequent instructions. In this case the first one sets it to '/diabetes-group06', while the second one sets the working directory to a subdirectory ('/webapp') of that set before
- **COPY:** it copies all the files and directories from the current directory (the directory where the Docker build command is run) to the working directory in the Docker image ('/diabetes-group06')
- **RUN:** it runs a Linux command. In this case the first one updates the package manager and installs any necessary packages, while the second one upgrades pip (the package installer for Python) and then installs the dependencies specified in the 'requirements.txt' file

- **EXPOSE:** it exposes ports informing Docker that the container will listen on the specified network port(s) at runtime. In this case it exposes the port 8501 that is the Streamlit default port
- **ENTRYPOINT:** it specifies the command to run when the Docker container is started. In this case, it runs the 'streamlit' command to start the application with the 'app.py' file as the main entry point. It also specifies the port to use (8501) and the server address to use (0.0.0.0).

Note that '**--server-address=0.0.0.0**' is used to allow the server inside the Docker container to listen on all available network interfaces, making it accessible from outside the container. Thanks to it, in this case, when the docker image is run the available URLs will become the same provided by Streamlit

To create the **Web App Docker image**, it is necessary to place in the root directory ('scc_group06') and run the following command:

```
docker build -t diabetes-group06 -f webapp/dockerfile .
```

```

PS C:\Users\Asdrubale\Desktop\scc_group06> docker build -t diabetes-group06 -f webapp/dockerfile .
[+] Building 66.4s (11/11) FINISHED
=> [internal] load build definition from dockerfile                                0.0s
=> => transferring dockerfile: 347B                                              0.0s
=> [internal] load .dockerignore                                                  0.0s
=> => transferring context: 2B                                                  0.0s
=> [internal] load metadata for docker.io/library/python:latest                 1.4s
=> [1/6] FROM docker.io/library/python@sha256:d3c16df33787f3d03b2e096037f6deb3c1c5fc92c57994a7d6f2de018de01a6b  0.0s
=> [internal] load build context                                                 0.1s
=> => transferring context: 8.72kB                                              0.1s
=> CACHED [2/6] WORKDIR /diabetes-group06                                       0.0s
=> [3/6] COPY . .                                                                3.0s
=> [4/6] WORKDIR /diabetes-group06/webapp                                       0.1s
=> [5/6] RUN apt-get update && apt-get install -y                             6.0s
=> [6/6] RUN pip install --upgrade pip && pip install -r requirements.txt       51.6s
=> exporting to image                                                            4.0s
=> => exporting layers                                                           3.9s
=> => writing image sha256:07774360ad1f933074f49ef89ee3b91059b0f86cd5c734fed653eef0f9f79628  0.0s
=> => naming to docker.io/library/diabetes-group06                             0.0s

Use 'docker scan' to run Snyk tests against images to find vulnerabilities and learn how to fix them
PS C:\Users\Asdrubale\Desktop\scc_group06>

```

Then it is possible to see the built image whether running the `docker images` command or going to the Docker Desktop application in Images section.

```

PS C:\Users\Asdrubale\Desktop\scc_group06> docker images
REPOSITORY    TAG       IMAGE ID   CREATED   SIZE
diabetes-group06 latest    5f28ba231c12   3 minutes ago   4.06GB
PS C:\Users\Asdrubale\Desktop\scc_group06>

```

Name	Tag	Status	Created	Size	Actions
diabetes-group06 5f28ba231c12	latest	Unused	3 minutes ago	4.05 GB	[Play] [Menu] [Trash]

To run the Web App Docker image in a **Docker container** it is possible to use the following command:

```
docker run --name diabetes-group06 -p 8501:8501 diabetes-group06
```

```

PS C:\Users\Asdrubale\Desktop\scc_group06> docker run --name diabetes-group06 -p 8501:8501 diabetes-group06

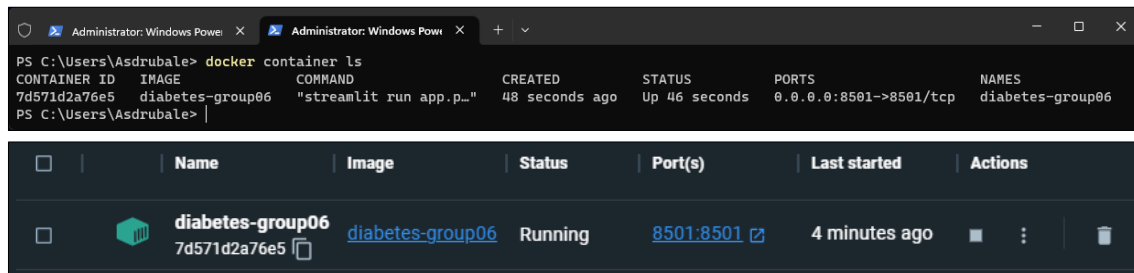
Collecting usage statistics. To deactivate, set browser.gatherUsageStats to False.

You can now view your Streamlit app in your browser.

URL: http://0.0.0.0:8501

```

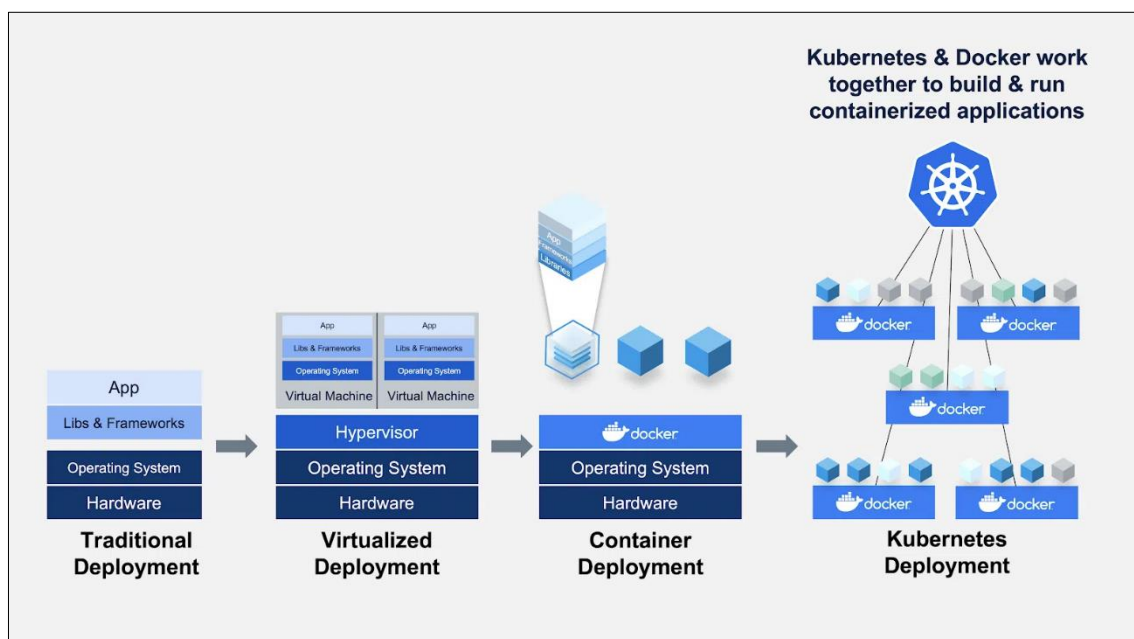
Then it is possible to see the run container whether running the `docker container ls` command or going to the Docker Desktop application in Containers section.



4.2.2. Kubernetes

Kubernetes is a popular open-source container orchestration platform that provides several advantages for deploying web applications. Here are some of the benefits of using Kubernetes to deploy a web app:

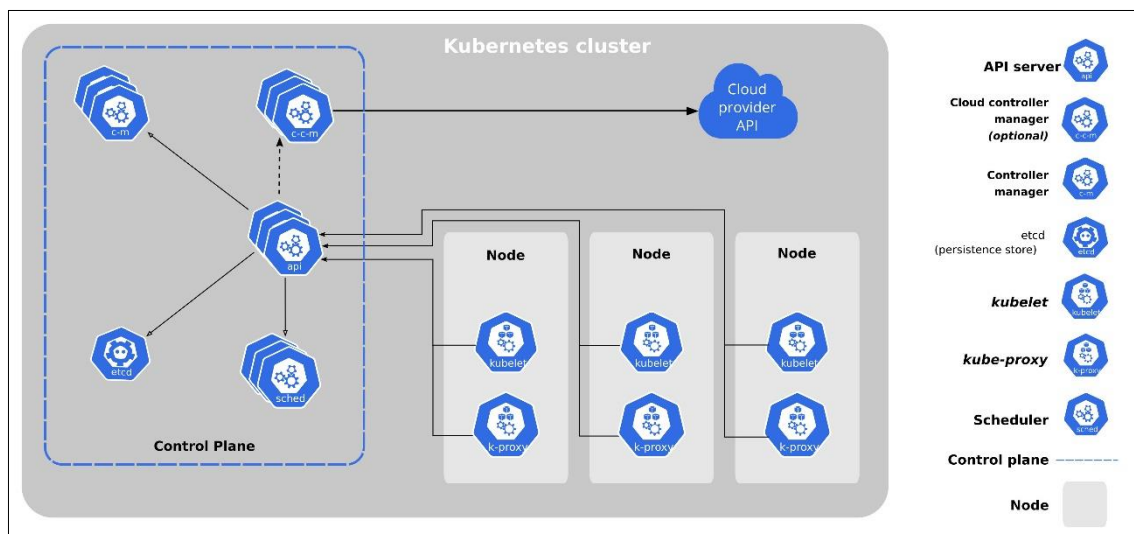
- **Scalability:** Kubernetes enables you to easily scale your web application by adding or removing containers as required. It can automatically adjust the number of containers based on traffic or resource utilization, ensuring that your application can handle high traffic loads
- **High availability:** Kubernetes provides automatic failover and rescheduling of containers in case of failures, ensuring that your web application is always available to users
- **Disaster recovery:** Kubernetes provides a process of restoring a system or application after a catastrophic event
- **Simplified deployment:** Kubernetes provides a declarative approach to deploying applications, making it easier to manage and deploy updates to your web application. It also supports rolling updates, allowing you to update your application without downtime
- **Portability:** Kubernetes provides a standardized way of deploying and managing containers, making it easy to move your web application across different environments, such as from development to production
- **Extensibility:** Kubernetes is highly extensible, with a large ecosystem of plugins and tools that can be used to extend its functionality



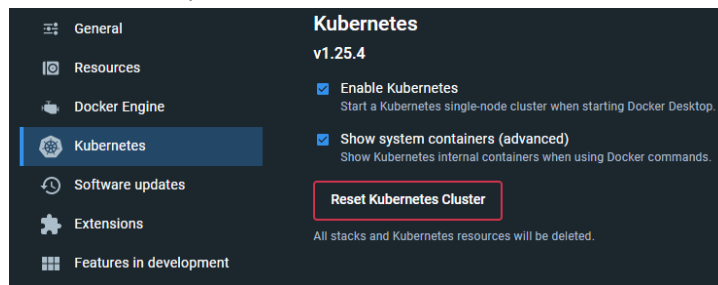
The **architecture** of Kubernetes can be broken down into several components:

- **Control Plane:** The control plane is the brain of Kubernetes, responsible for managing the entire system. It consists of several components that work together to orchestrate the deployment and management of containerized applications. The main components of the control plane are:
 - **API Server:** it is the central component of the control plane, which exposes the Kubernetes API for managing the system
 - **etcd:** it is a distributed key-value store used by Kubernetes to store all the configuration and state information of the system
 - **Scheduler:** it is responsible for scheduling containers to run on specific nodes based on their resource requirements and availability
 - **Controller Manager:** it is responsible for managing the lifecycle of Kubernetes objects, such as Pods, Services, and Replica Sets
- **Nodes:** Nodes are the worker machines in Kubernetes, responsible for running containerized applications. Each node runs a container runtime, such as Docker, to manage containers. The main components of a node are:
 - **kubelet:** it is an agent that runs on each node and communicates with the control plane to manage containers on the node
 - **kube-proxy:** it is responsible for managing network connectivity between containers on the same node and between nodes
- **Objects:** Kubernetes objects are the building blocks of the system, representing the desired state of a particular resource, such as a Pod, Service, or Replication Controller. Some of the key objects in Kubernetes are:
 - **Pod:** it is the smallest deployable unit in Kubernetes, representing one or more containers that run together on a single node
 - **Service:** it provides a stable IP address and DNS name for a set of Pods, enabling other components to discover and communicate with them
 - **Replica Set:** it ensures that a specified number of replicas of a Pod are running at all times

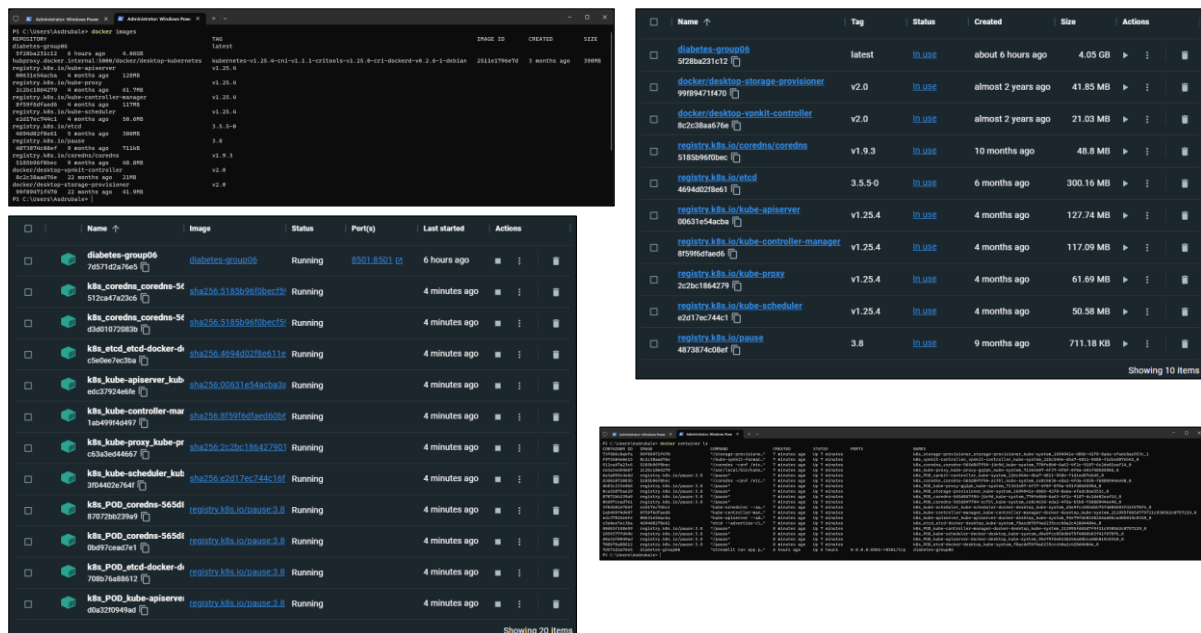
Note that while nodes are the physical machines where containers run, objects are the logical abstractions that represent different components of your application. Nodes are managed by the Kubernetes system, whereas objects are created and managed by users or applications. In other words, nodes are the infrastructure that supports objects, and objects are the applications that run on nodes.



To have a Kubernetes cluster running on a local machine it is necessary to **enable Kubernetes** on Docker Desktop.



At this point all necessary Kubernetes images and containers are visible through the ways already seen in the previous section.



In Kubernetes, a **manifest file** is a YAML file that permits to configure the desired state of a Kubernetes object, such as a Pod, deployment, service, or replication controller. The manifest file specifies the configuration of the object, including its metadata, specifications, and optionally, any other relevant information. Manifest files are used by Kubernetes to deploy and manage applications in a declarative manner.

Alongside it is described the functionality of each part of the manifest file.

This file defines a Kubernetes deployment and service for a containerized application named 'diabetes-group06'.

The **deployment section** specifies the name of the deployment as 'diabetes-group06-deployment' and that it will run 5 replicas of the 'diabetes-group06' container image, using a selector to match the labels with the 'app: diabetes-group06'.

The **template subsection** specifies the configuration for the Pod that will be created for the deployment. It has a single container, also named 'diabetes-group06', with an imagePullPolicy set to 'Never', which means that the container image should be available on the node before the Pod starts running.

The **service section** creates a Kubernetes service that exposes the deployment to the external world. It specifies the name of the service as 'diabetes-group06-service' and sets the type to 'NodePort'. The selector is set to match the labels with the 'app: diabetes-group06', which means that it will route traffic to the Pods with the matching label. The ports section maps the container port 8501 to the target port 8501 and sets the nodePort to 30005.

Note that it was used 'NodePort' as type of the service because it is the easiest way to expose a service to external traffic, but it's not as scalable or secure as the other types of service exposure (Load Balancer or ClusterIP with an Ingress controller).

To deploy the manifest file it is necessary to place in the webapp directory and run the following command:

```
kubectl apply -f manifest.yaml
```

```
Administrator: Windows PowerShell
PS C:\Users\Asdrubale\Desktop\scc_group06\webapp> kubectl apply -f .\manifest.yaml
deployment.apps/diabetes-group06-deployment created
service/diabetes-group06-service created
PS C:\Users\Asdrubale\Desktop\scc_group06\webapp>
```

To check the created Pods, its IP addresses and the node on which they are running it is possible to run the following command:

```
kubectl get Pods -o wide
```

```
Administrator: Windows PowerShell
PS C:\Users\Asdrubale\Desktop\scc_group06\webapp> kubectl get pods -o wide
NAME                                READY   STATUS    RESTARTS   AGE   IP            NODE           NOMINATED NODE   READINESS GATES
diabetes-group06-deployment-78c78b9449-j5wpp    1/1     Running   0           2m17s  10.1.0.60     docker-desktop    <none>           <none>
diabetes-group06-deployment-78c78b9449-jx828    1/1     Running   0           2m17s  10.1.0.63     docker-desktop    <none>           <none>
diabetes-group06-deployment-78c78b9449-qpc8k    1/1     Running   0           2m17s  10.1.0.59     docker-desktop    <none>           <none>
diabetes-group06-deployment-78c78b9449-rzk14    1/1     Running   0           2m17s  10.1.0.61     docker-desktop    <none>           <none>
diabetes-group06-deployment-78c78b9449-zmkt6    1/1     Running   0           2m17s  10.1.0.62     docker-desktop    <none>           <none>
```

```
webapp > manifest.yaml > {} spec > {} ports > {} 0 > # nodePort
1
2 kind: Deployment
3
4 metadata:
5   name: diabetes-group06-deployment
6   namespace: default
7 spec:
8   replicas: 5
9   selector:
10    matchLabels:
11      app: diabetes-group06
12 template:
13   metadata:
14     labels:
15       app: diabetes-group06
16   spec:
17     containers:
18       - name: diabetes-group06
19         image: diabetes-group06
20         imagePullPolicy: Never
21 ---
22
23 apiVersion: v1
24 kind: Service
25 metadata:
26   name: diabetes-group06-service
27   namespace: default
28 labels:
29   app: diabetes-group06
30 spec:
31   type: NodePort
32   selector:
33     app: diabetes-group06
34   ports:
35     - port: 8501
36       targetPort: 8501
37       nodePort: 30005
```


To check the running deployments it is possible to run the following command:

```
kubectl get deployments
```

```
Administrator: Windows PowerShell
PS C:\Users\Asdrubale\Desktop\scc_group06\webapp> kubectl get deployments
NAME                                READY    UP-TO-DATE    AVAILABLE    AGE
diabetes-group06-deployment         5/5      5              5            4m10s
PS C:\Users\Asdrubale\Desktop\scc_group06\webapp>
```

To check the running services it is possible to run the following command:

```
kubectl get services
```

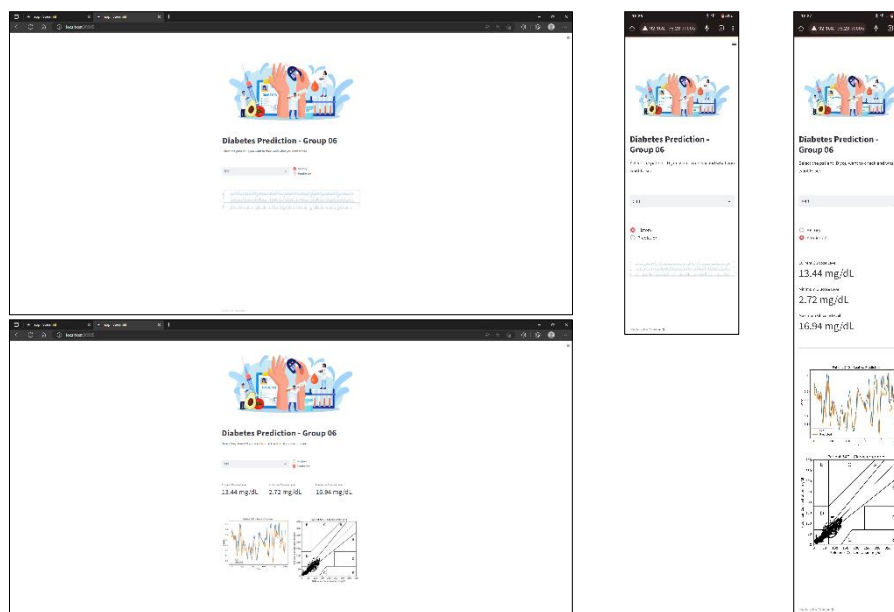
```
Administrator: Windows PowerShell
PS C:\Users\Asdrubale\Desktop\scc_group06\webapp> kubectl get services
NAME                                TYPE        CLUSTER-IP    EXTERNAL-IP    PORT(S)    AGE
diabetes-group06-service            NodePort     10.109.14.154 <none>         8501:30005/TCP 4m46s
kubernetes                          ClusterIP    10.96.0.1     <none>         443/TCP    5d22h
PS C:\Users\Asdrubale\Desktop\scc_group06\webapp>
```

To get more information about a service it is possible to run the following command:

```
kubectl describe services diabetes-group06-service
```

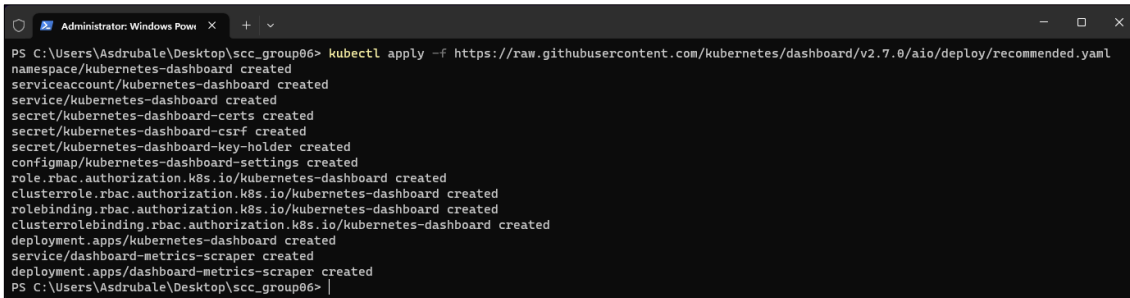
```
Administrator: Windows PowerShell
PS C:\Users\Asdrubale\Desktop\scc_group06\webapp> kubectl describe services diabetes-group06
Name: diabetes-group06-service
Namespace: default
Labels: app=diabetes-group06
Annotations: <none>
Selector: app=diabetes-group06
Type: NodePort
IP Family Policy: SingleStack
IP Families: IPv4
IP: 10.109.14.154
IPs: 10.109.14.154
LoadBalancer Ingress: localhost
Port: <unset> 8501/TCP
TargetPort: 8501/TCP
NodePort: <unset> 30005/TCP
Endpoints: 10.1.0.59:8501,10.1.0.60:8501,10.1.0.61:8501 + 2 more...
Session Affinity: None
External Traffic Policy: Cluster
Events: <none>
PS C:\Users\Asdrubale\Desktop\scc_group06\webapp>
```

To visualize the local deployed Web App it is possible to use the same URLs provided by Streamlit and also used by Docker with the difference that nodePort has to be used and it is 30005.



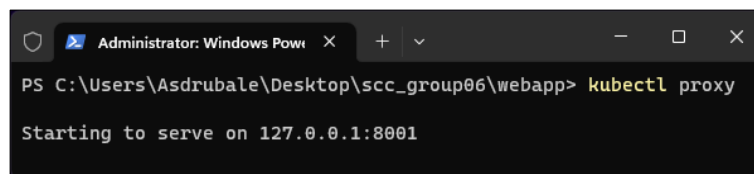
To visualize the **Kubernetes Web Dashboard** it is necessary to run the following commands:

```
- kubectl apply -f https://raw.githubusercontent.com/kubernetes/dashboard/v2.7.0/aio/deploy/recommended.yaml
```



```
Administrator: Windows Pow...
PS C:\Users\Asdrubale\Desktop\scc_group06> kubectl apply -f https://raw.githubusercontent.com/kubernetes/dashboard/v2.7.0/aio/deploy/recommended.yaml
namespace/kubernetes-dashboard created
serviceaccount/kubernetes-dashboard created
service/kubernetes-dashboard created
secret/kubernetes-dashboard-certs created
secret/kubernetes-dashboard-csrf created
secret/kubernetes-dashboard-key-holder created
configmap/kubernetes-dashboard-settings created
role.rbac.authorization.k8s.io/kubernetes-dashboard created
clusterrole.rbac.authorization.k8s.io/kubernetes-dashboard created
rolebinding.rbac.authorization.k8s.io/kubernetes-dashboard created
clusterrolebinding.rbac.authorization.k8s.io/kubernetes-dashboard created
deployment.apps/kubernetes-dashboard created
service/dashboard-metrics-scraper created
deployment.apps/dashboard-metrics-scraper created
PS C:\Users\Asdrubale\Desktop\scc_group06> |
```

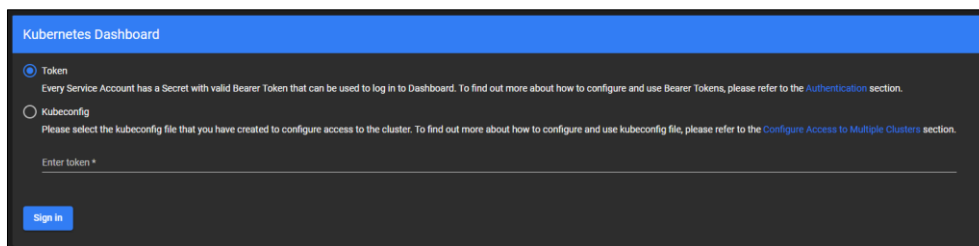
```
- kubectl proxy
```



```
Administrator: Windows Pow...
PS C:\Users\Asdrubale\Desktop\scc_group06\webapp> kubectl proxy
Starting to serve on 127.0.0.1:8001
```

and connect to the following browser link:

<http://localhost:8001/api/v1/namespaces/kubernetes-dashboard/services/https:kubernetes-dashboard:/proxy/#/login>



At this point an enter token it is requested and to obtain it an admin user must be created. To do this it is necessary to create a '.yaml' file (usually named 'dashboard-adminuser').

Alongside it is described the functionality of each part of the file.

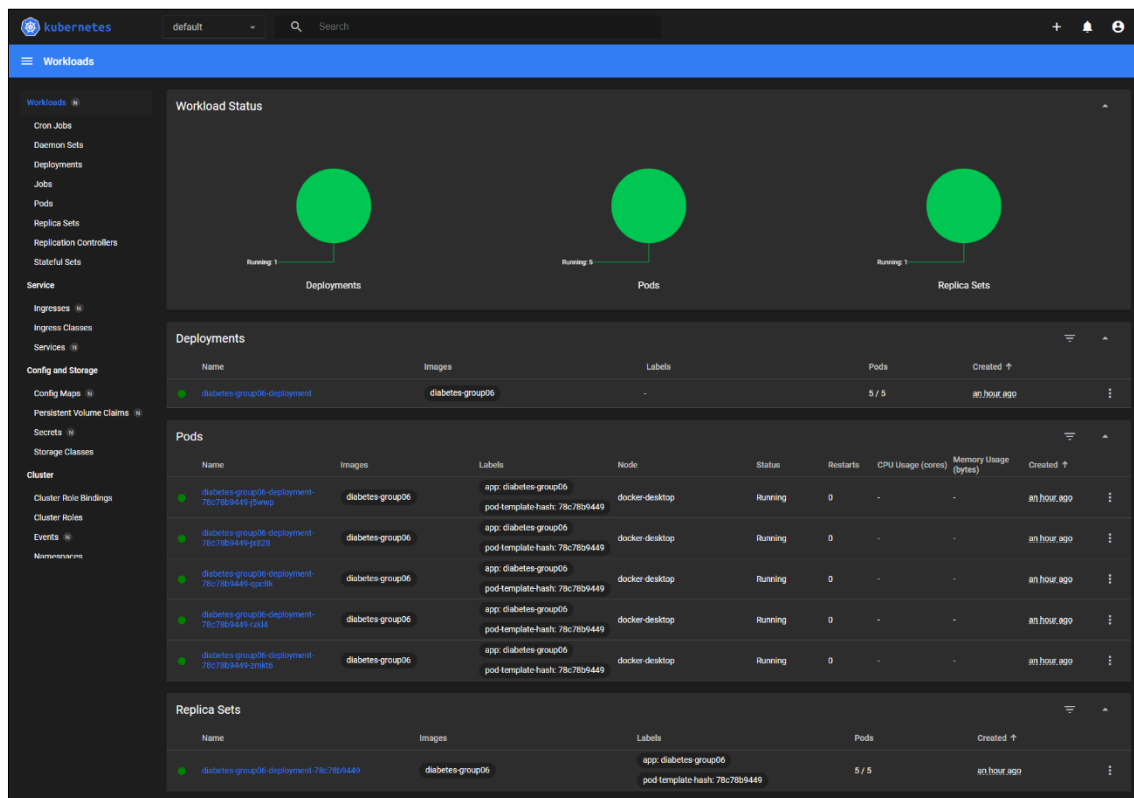
This Kubernetes file defines a **ServiceAccount** named admin-user in the kubernetes-dashboard namespace and a **ClusterRoleBinding** named admin-user that binds the cluster-admin role to the admin-user service account.

The ServiceAccount resource defines an identity for a Pod or set of Pods, allowing them to authenticate and interact with the Kubernetes API server. The metadata section specifies the name of the service account (admin-user) and the namespace where it is created (kubernetes-dashboard).

The ClusterRoleBinding resource binds a role to a subject, which can be a user, group, or service account. In this case, the roleRef section specifies that the cluster-admin role from the rbac.authorization.k8s.io API group should be used. The subjects section specifies that the role should be bound to the admin-user service account in the kubernetes-dashboard namespace.

```
webapp > dashboard-adminuser.yaml > [ ] subjects > {} 0 > namespace
1  apiVersion: v1
2  kind: ServiceAccount
3  metadata:
4    name: admin-user
5    namespace: kubernetes-dashboard
6
7  ---
8
9  apiVersion: rbac.authorization.k8s.io/v1
10 kind: ClusterRoleBinding
11 metadata:
12   name: admin-user
13 roleRef:
14   apiGroup: rbac.authorization.k8s.io
15   kind: ClusterRole
16   name: cluster-admin
17 subjects:
18 - kind: ServiceAccount
19   name: admin-user
20   namespace: kubernetes-dashboard
```


Once copied and pasted the token in the browser page seen before it is possible to access the Kubernetes dashboard.



According with everything was said about Kubernetes advantages, when you edit the **'manifest.yaml'** file to increase the number of replicas for a Kubernetes deployment, Kubernetes will automatically handle the scaling up of the deployment. Kubernetes will create new Pods and ensure that the specified number of replicas are running. Similarly, if you update the image of your application in the manifest file, Kubernetes will automatically create new Pods with the updated image and terminate the old Pods running the previous one.

Kubernetes uses the desired state configuration model, which means that the manifest file defines the desired state of the deployment or service and ensures that the current state matches the desired state by making the necessary changes in real time. This makes it easy to scale up or update your application without having to manually create or delete Pods.

4.3. Further information

For the correct functioning of the Web App and its deployment it was created the **'webapp' directory** of the project characterized by the structure represented below.

```
C:.\
  app.py
  dashboard-adminuser.yaml
  diabetes.jpg
  dockerfile
  manifest.yaml
  requirements.txt
  utils.py
```

5. Security

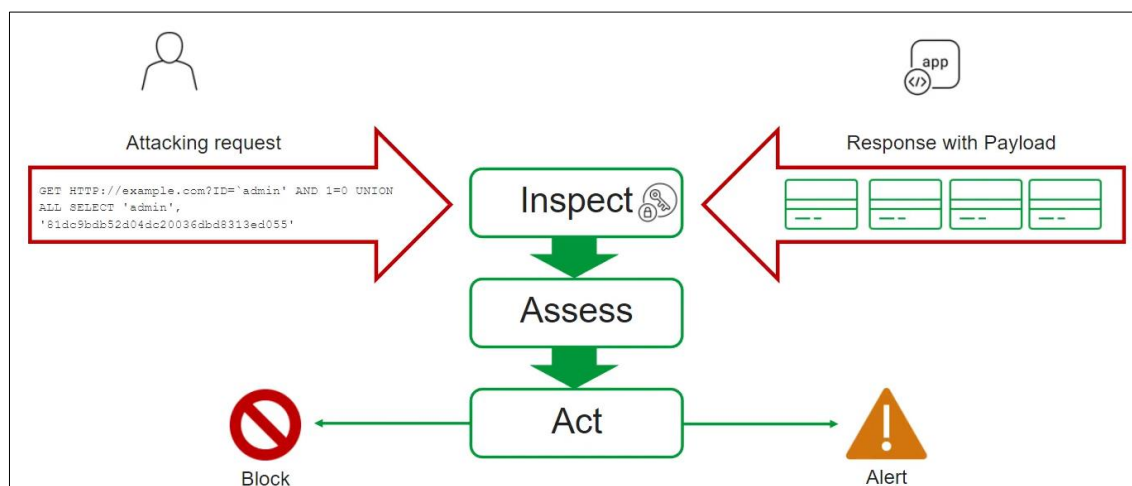
The security of cloud technology, such as Kubernetes containers, is a **major challenge**. **NGINX**, an open-source web server, has evolved from its initial success as a server to become a reverse proxy, HTTP cache, and Load Balancer. In terms of security, there is no difference between a monolithic application running on a virtual machine and a microservices-based application running on Kubernetes, as both are vulnerable to any type of attack, including DDoS attacks.

	Monolithic application running on a virtual machine	A Microservices based application in Kubernetes
Application layer vulnerability exploit	✓	✓
Application layer DDoS attacks	✓	✓

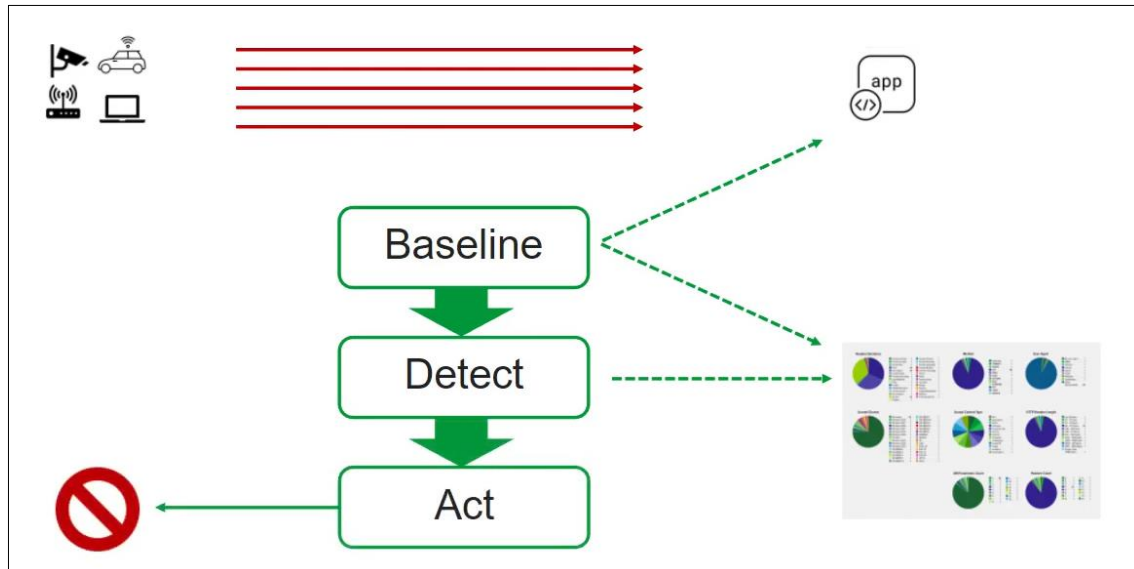
To protect applications from these attacks, it is necessary to consider vulnerabilities in the application layer. Suppose there is a GET request attack (e.g. random SQL injection) that is about to compromise data (e.g. credit card numbers).

To **prevent and mitigate** the attack it is needed something in the middle between client and server that can decipher/inspect the code at the application level, rather than the packet level. Once the code has been inspected, it is necessary to evaluate it to determine whether it is malicious or not, and this should also be possible with the response. An attack does not pose a threat until the request receives a response or crashes the running processes.

After evaluating the request and/or response, it is necessary to block, alert, or do nothing. In the case of blocks, the connection should not be closed because it would render the application unreachable, and if it was a false positive, we would have prevented correct functioning. A response of 'this request has been blocked' should be sent so that the sender can then contact us and request information to allow us to investigate the incident.



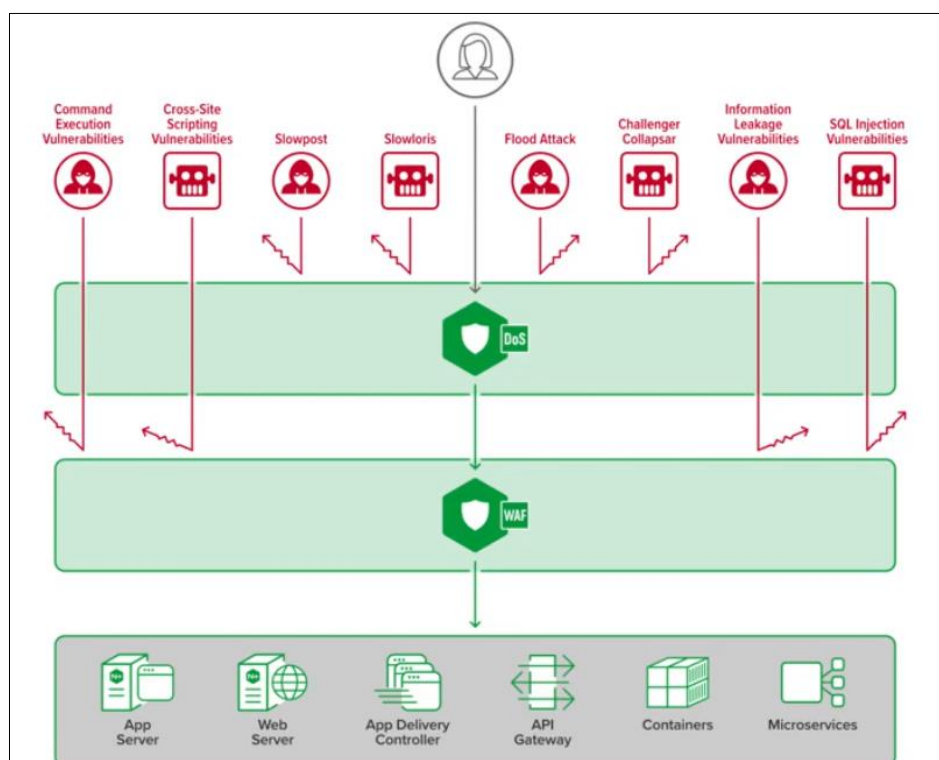
Mitigating DDoS attacks at the application level requires working slightly differently. The first thing to do is to build a baseline, that is how the application should behave because this is the best way to detect DDoS attacks as they modify correct functioning by slowing down the connection. The baseline can detect that there are problems and that the server has become slower in responding. Once an attack is detected, appropriate action can be taken.



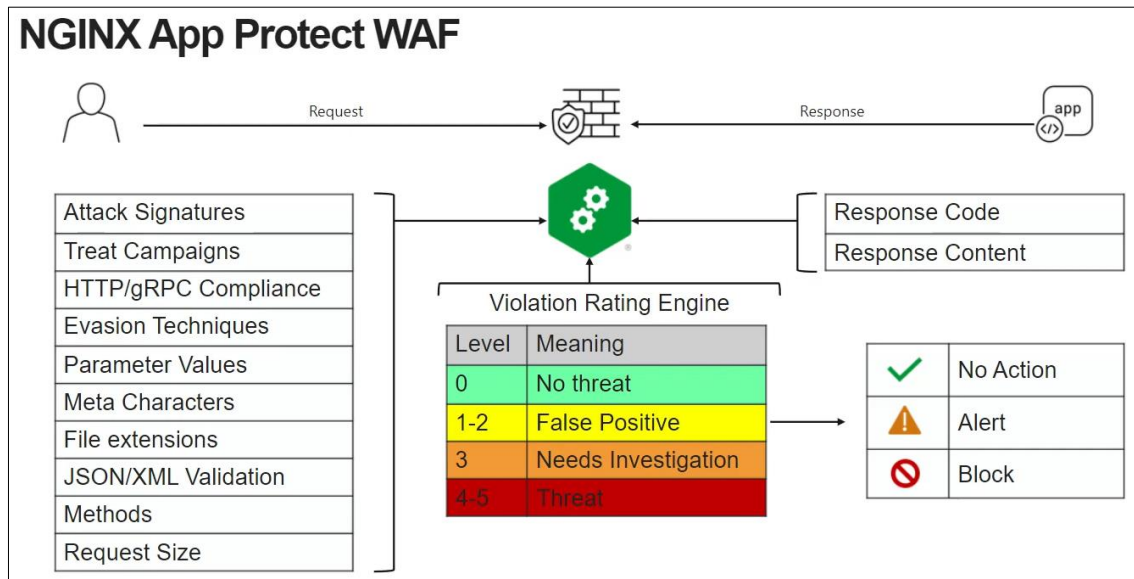
To solve these types of problems, 2 add-on modules are presented:

- **NGINX App Protect WAF**
- **NGINX App Protect DoS**

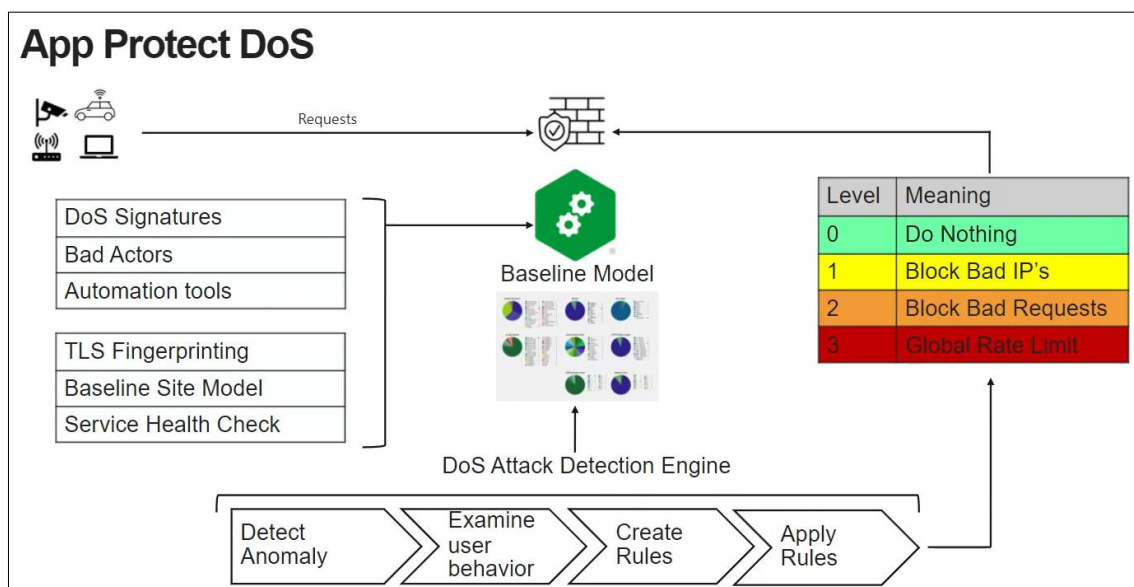
These modules can be used in Kubernetes to enhance security.



NGINX App Protect WAF is responsible for **monitoring requests and responses**. Monitoring is done by specifying the items shown in the image below. For each request and response, a level of risk is assigned through the **Violation Rating Engine**. Based on the level, anyone using this add-on can configure actions to decide whether to block, alert, or do nothing. There may be false positives, but tests suggest the probabilities are low.



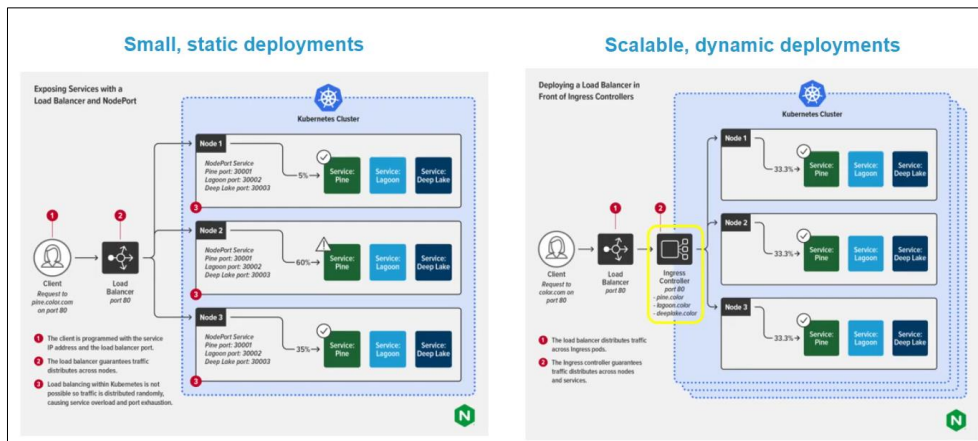
On the other hand, NGINX App Protect DoS is responsible for **monitoring DoS attacks**. As previously mentioned, the first step in protecting against DoS attacks is to **create a baseline**. The add-on acts on this baseline to detect and notify any changes/anomalies based on what is shown in the image below. Once an anomaly is detected, it must examine user behavior to understand the cause. Specifically, it must check incoming traffic to understand the pattern, where it comes from, what type of request it is, and then dynamically create a rule to detect bad traffic. Rules should not be created through hand-written code, but rather dynamically created and applied. The application of such rules should occur according to the rules chosen based on the needs.



There are various ways to expose services, or applications, with Kubernetes.

The most popular method is to use a Load Balancer and NodePort, but this method suffers from disadvantages when dealing with large deployments because load balancing with many IP addresses can take a long time. Additionally, this method does not guarantee some interesting features such as TLS encryption and rate limiting.

Another method is to use a Load Balancer and the Ingress controller. The controller can be synchronized with Kubernetes or with NGINX, and in this way, we can expose any application of any size and have the additional features that we did not have before.



Application deployment in a monolithic architecture does not happen very frequently, while in microservices, it happens more frequently. When updating or deploying a monolithic application, it is done manually or with a patch, while in Kubernetes or a microservices-centered architecture, it is done with a redeploy, rolling, or canary.

	Monolithic application running on a virtual machine	A Microservices based application in Kubernetes
Deployment Frequency	Infrequent	Frequent
Update/Deployment Methods	Patched/Manual update	Redeploy/Rolling/Canary

The advantages of having a Nginx Ingress controller with Nginx App Protect are that it reduces complexity in the environment, making it easier to manage. Nginx Ingress Controller has other advantages over Kubernetes Ingress controller, such as the possibility to have customized Nginx resources and be easily natively deployed on the cloud. Furthermore, as already mentioned, it introduces policy objects, TLS encryption, etc.

