Multi-layer Perceptron application for muon identification in CBM experiment at FAIR

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Declaration

I, Raktim Mukherjee, hereby declare that this thesis entitled "Multi-layer Perceptron application for muon identification in CBM experiment at FAIR" under the supervision of Dr. Subhankar Ghosh and Prof. Subhasis Chattopadhyay, during the academic year 2022-2023 is the result of my original research work and has not been submitted earlier, in part or in full, for the award of any other degree or diploma. The work presented in this thesis is my own and all sources of information and materials used in this research have been duly acknowledged and referenced.

Raktim Mukherjee

Dedicated to my parents,

my grandparents

and
my German Shepherd, Planck

Synopsis

After high-energy heavy ion collision experiments when various particles enter a detector, it becomes necessary to separate the signal from the background. We obtain a huge amount of data when this happens and with a lot of features. In other words, we obtain data with a high dimensionality. This is true for any experiment involving particle detection. To separate the background from the signal we need to use graphical cuts. But due to the high dimensionality, the optimisation of all the features becomes difficult. Hence, we do this using a *multi-layer perceptron model* (MLP) which is basically an Artificial Neural Network (ANN) that has been trained for this purpose.

The *Facility for Anti-proton and Ion Research* (FAIR) will conduct the Compressed Baryonic Matter (CBM) experiment to investigate the QCD phase diagram in the high net-baryon density region. Currently, ω is one of the lightest vector mesons that can be detected using the CBM setup. For this thesis, an 8 A GeV Au + Au collision has been simulated using the Monte Carlo technique which abundantly generates various vector mesons, the ω-meson being of our interest as this gives abundant information about the fireball. I will be using the muons from the decay

$$\omega \rightarrow \mu^+ + \mu^-$$

(which is our signal) as they are weakly interacting (approx 0.5 GeV) and hence give a higher number of hits in the various layers of the detector. The main aim of this project is to train the MLP using the dataset containing such muons to obtain the parameter which can be used to place the cuts in experimental data in order to easily separate the muons from the background. To detect di-muons in the CBM experiment, which is a penetrating probe for the reaction zone, a novel technique using a set of segmented absorbers and high granularity detectors sandwiched between the absorber pairs has been developed and is being built at *VECC*-Kolkata. The absorber will absorb hadrons while allowing muons to pass through. In this ANN technique, inputs involving various detector parameters and track properties will be used to enrich the di-muon samples.

Contents

1 Introduction

With the advancement of particle accelerators, the energy involved in collision experiments has increased. Such advancement has led to a huge amount of particle production and consequently the data. The CBM experiment will focus on strong interactions by generating collision rates around 10 MHz. They plan on doing so without using any hard triggers which will result in a data rate of approximately 1 TB/s [1]. This makes the task of separating the signal from the background manually very challenging. This is where the role of an *Artificial Neural Network* (ANN) comes in. If we train our ANN using simulated data, then the ANN *learns* the expected behaviour of the signal. We can then use this model as many times as we want for actual experimental data for the separation of signal from background.

The omega can decay into any di-lepton channel and there are also other sources of di-leptons in this experiment. In this particular paper, I train a multi-layer perceptron using the di-muons produced in the decay of an ω-meson and some hadronic background channels. The model is trained using four features

1. `STS_hits`: The number of hits in the Silicon Tracking System
2. `MUCH_hits`: The number of hits in the Muon Chamber
3. `chi_STS`: The standard deviation of the reconstructed path of the muon in the Silicon Tracking System
4. `chi_MUCH`: The standard deviation of the reconstructed path of the muon in the Muon Chamber.

The details of STS and MuCh, which are part of the CBM detector, have been discussed in section 2.2. The MLP returns an output parameter after optimisation of each of the above features. Graphical cuts will be used on this parameter to separate the signal from the background. We need to separate these di-muons in order to calculate their invariant mass which in turn will help to determine the mass of the ω-meson.

2 The CBM experiment

The Compressed Baryonic Matter experiment, aka CBM, is a large-scale international research project aimed at studying the properties of nuclear matter at extreme conditions of temperature and density. The experiment is based at the Facility for Antiproton and Ion Research (FAIR) in Darmstadt, Germany, which is still under construction.

The QCD phase diagram of nuclear matter, figure 1, describes the different states of matter under different temperature and density conditions. The primary goal of the CBM experiment is to investigate the low temperature and high net-baryon density region. This will help us to understand the properties of the core of neutron stars.

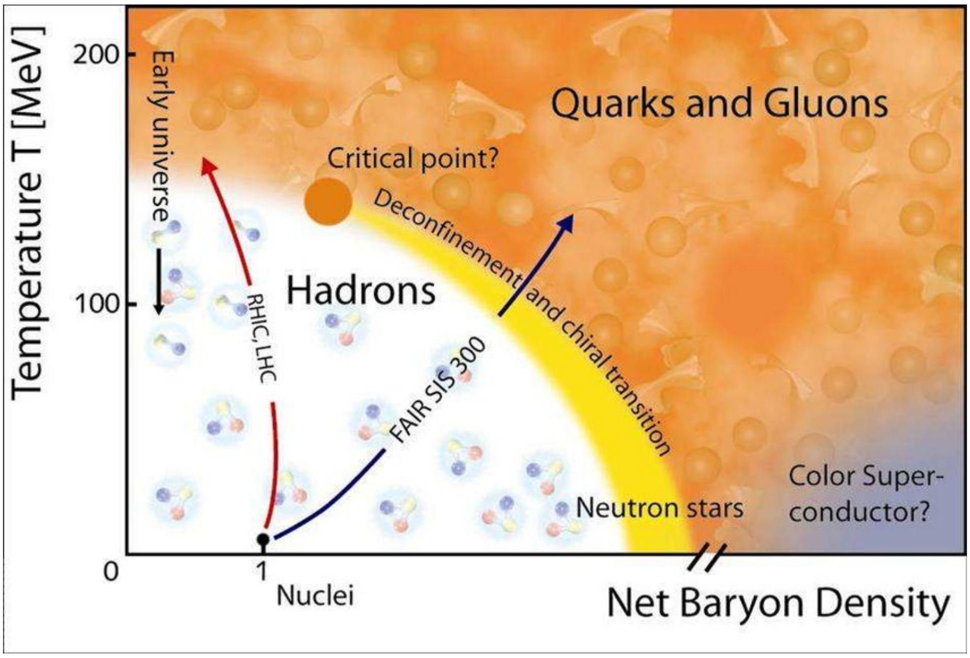


Figure 1: A possible sketch of the QCD phase diagram [2]

To achieve this goal, the CBM experiment will use heavy-ion collisions, in which two atomic nuclei are collided with each other at high energies, to create a state of matter called the quark-gluon plasma (QGP) which will allow us to probe the phase diagram of the nuclear matter at different temperatures and baryonic densities. One such probe is detecting di-lepton which are decay products of particles with charm quarks and vector mesons [3]. In this project, the focus will be on the detection such di-leptonic decay of the ω-meson.

By studying the properties of the QGP, the CBM experiment aims to shed light on several vital questions in nuclear physics, such as the nature of the phase transition from hadronic matter (matter composed of protons and neutrons) to the QGP, the equation of state of nuclear matter at high densities, and the transport properties of the QGP. These studies will provide important insights into the behavior of nuclear matter under extreme conditions, and help us to better understand the nature of matter in the universe.

2.1 The Physics behind the experiment

The fireball created by colliding heavy ions at high energies can mimic the quark-gluon phase of the early universe. But the quark-gluon plasma (QGP) is extremely short-lived (a few fermi/c) and hence cannot be studied directly. We use can use rare probes like ρ, ω, and J/ψ. These vector mesons carry information regarding the early phase of the fireball.

Another way is by studying the thermally emitted photons and di-leptons from the QGP [4]. An exceptional chance to comprehend the characteristics of strongly interacting matter is provided by the di-leptons produced in high-energy heavy-ion collisions. Over the system's entire time evolution, nuclear collisions emit electromagnetic radiation (virtual photons). Once created, these photons decay into di-electron or di-muon channels. Thus, research into these leptonic decay channels can reveal details about the fireball's extreme temperatures and density. The mean free path of photons(10^2-10^4 fm) is significantly larger than the fireball size (approx 10 fm) at the maximum temperature and density, preventing further interaction and allowing them to carry information about the system's original state [5]. These photons and leptons give us an idea about the average temperature of the system during the collision. Di-leptons are emitted at every stage of the heavy-ion collisions and from different sources. The invariant mass (M) and the transverse momentum (p_T) of the di-leptons can help us study the different stages of the fireball. The di-leptons with high M and (p_T) come from the early phase whereas the ones with low M and (p_T) are produced at a later phase when the temperature is lower.

The common sources of such di-leptons are the annihilation of quark anti-quark, Compton scattering, direct decay from hadronic resonances like ρ, ϕ, ω, and J/ψ, etc. Dren-Yall processes and Dalitz decay also contribute to this [5].

2.2 The experimental setup

The Facility for Anti-proton and Ion Research in Darmstadt, Germany is still being built and when completed will look like figure 3. We can see that this facility not only hosts the CBM experiment but also three other experiments PANDA (detector for hadron physics), NUSTAR (for nuclear and astrophysics) and APPA (different applications of atomic and plasma physics).

We see the SIS100 accelerator ring in the picture which is a synchrotron with a magnetic rigidity of 100 Tm. The beam from SIS100 will be fed into the CBM detector.

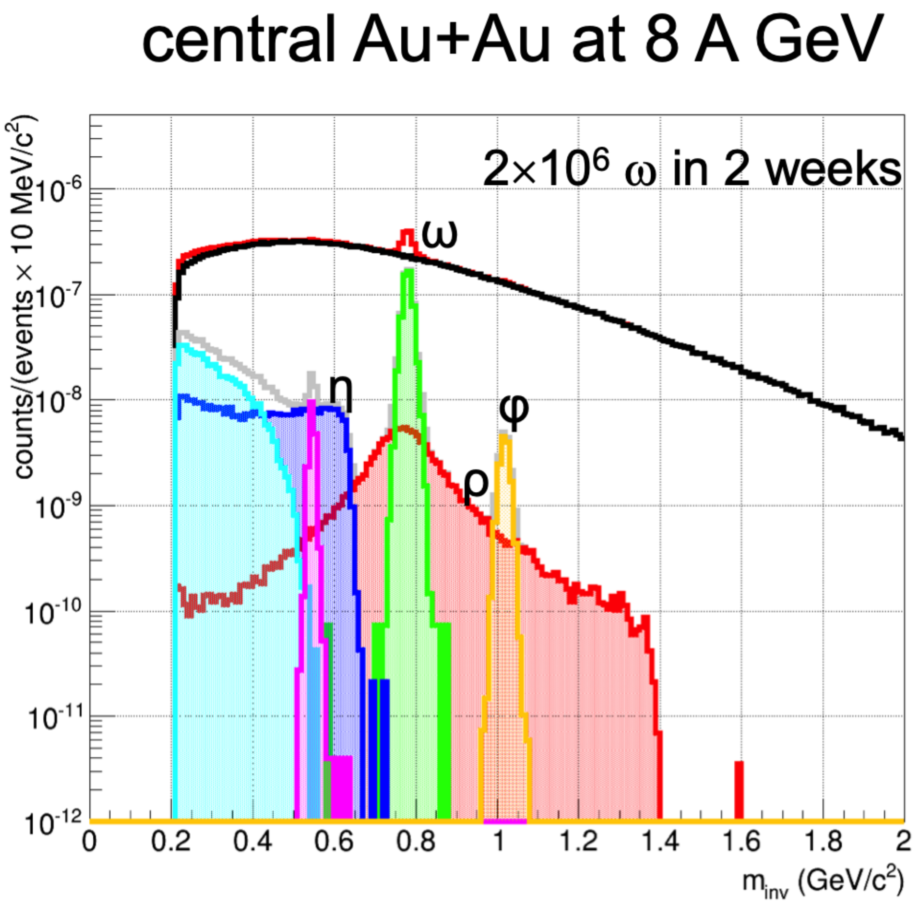


Figure 2: Cocktail of the expected vector mesons [6]

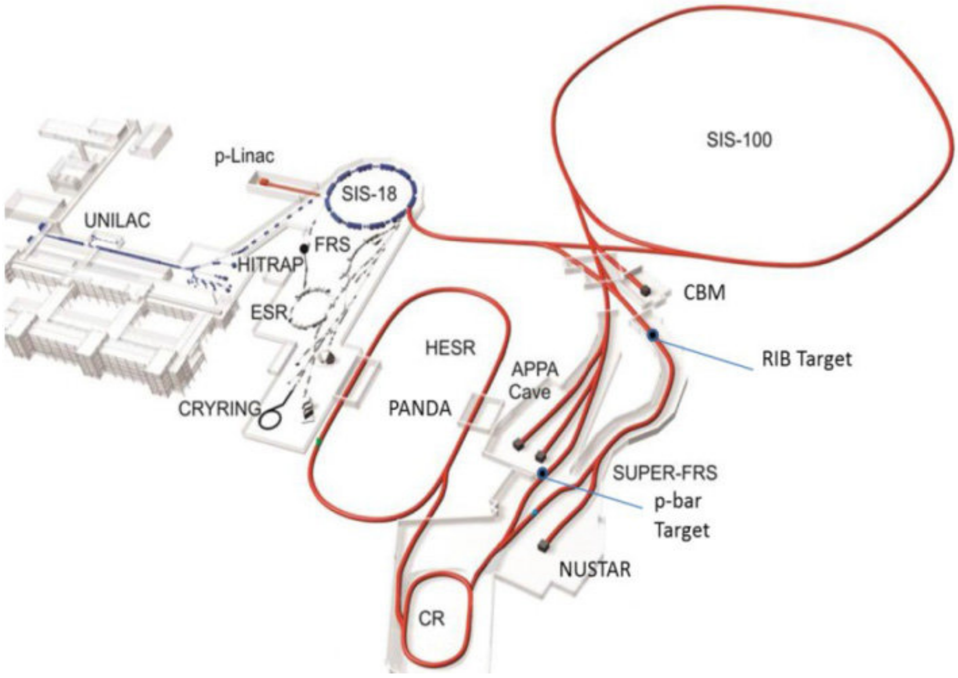


Figure 3: The Layout of the existing GSI facilities and the upcoming FAIR project [7]

The beam will then enter the setup shown in figure 4. The beam will pass through the Silicon Tracking System (STS), Muon Chamber (MuCh), Transition Radiation Detector (TRD) and Time of Flight detector (TOF, not shown in the figure)[1] .**The scope of the project is limited to the detection of di-muon from omega for which the STS and MuCh are sufficient**.

2.2.1 Silicon Tracking System

The STS is placed inside 2 superconducting dipole magnets of magnetic field 1 Tm. The STS consists of 8 tracking layers and is aimed at measuring the momentum of the charged particles. The charged particles experience the magnetic fields and are diverted from their initial trajectory vertically up or down (depending on the charge). The `STS_hits` gives the count of the number of layers of the STS the muon penetrated through and `chi_STS` is the amount by which the reconstructed path has deviated from the actual path. The STS and the MuCh are separated by an absorber consisting of 28 cm of low-density graphite ($\rho = 1.7g/cm^3$) and 30 cm concrete.

[1]In place of the MuCh it may have RICH (Ring Imaging Cherenkov detector) for detecting di-electrons. Both can't be present at the same time. This is a disadvantage of fixed-target experiments.

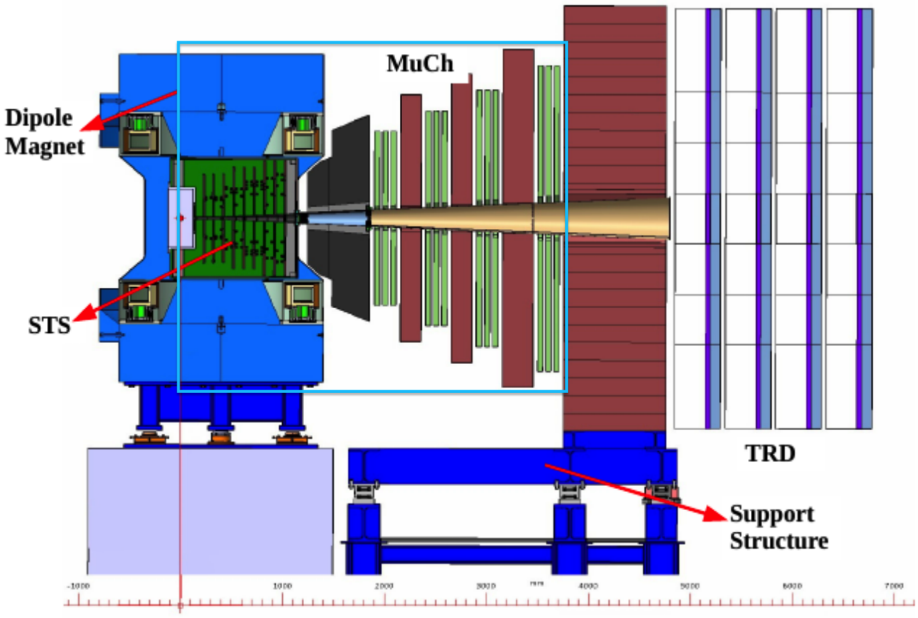


Figure 4: The CBM experiment setup with the Muon Chamber [5], the blue box marks the scope of this project

2.2.2 Muon Chamber

The muon chamber consists of 4 detectors (green in colour) and 4 absorbers (brown in colour) stations as can be seen in figure 4. The absorbers are made of iron. The first two detector stations consist of triplets of Gas Electron Multiplier (GEM), which are high-rate detectors and the next two have triplets of Resistive Plate Chamber (RPC). Therefore we have a total of 12 detector layers in MuCh. The `MUCH_hits` gives the count of the number of layers of the MuCh the muon penetrated through and `chi_MUCH` is the amount by which the reconstructed path has deviated from the actual path. These MuCh detectors are being built at the Variable Energy Cyclotron Centre, Kolkata.

3 Machine Learning: Key ideas for HEP applications

'Machine Learning' is an umbrella term to refer to the different algorithms which can make predictions when supplied with data. Such algorithms, also called *models* can either be trained with data with known outputs- *Supervised Learning* to predict outputs for new data or provide labels and find patterns in unlabelled data- *Unsupervised Learning.* The key idea behind any of the algorithms is the search for some function $f : \boldsymbol{X} \to \boldsymbol{Y}$ from the experimental space $\boldsymbol{X}$ to a low dimensional space of target label $\boldsymbol{Y}$ which optimises a metric of choice. Such a metric is called the loss function, $\boldsymbol{L}(\boldsymbol{y}, f(\boldsymbol{x}))$

The data collected from various HEP experiments are complex and high dimensional. Traditional data analysis techniques are based on the distribution of one of the observed variables at a time. This can't be easily extended to higher dimensions easily. Traditional algorithms to reduce the dimensionality include *track reconstruction* and *event selection*[8]. Hence, Machine learning algorithms were introduced for multivariate analysis. The commonly used ML algorithms are Kernel Density Estimation (KDE), Support Vector Machine (SVM), random forests and boosted decision trees. But these algorithms failed to impress when the dimensionality of the data increased to 5 or more. In such situations, Artificial Neural Networks showed the best performance[9]. The main task of ML in HEP is to improve data reduction by narrowing the relevant information contained in low-level high-dimensional data to high-level low-dimensional space[2].

3.1 Artificial neural network

As the name suggests, a *neural network* is a computational model inspired by the neural network in our body. An artificial neural network comprises two or more perceptrons(a layer of neurons), arranged to resemble the synaptic connections in our brain. A perceptron again consists of some neurons which are basically linear mathematical functions. Each such neuron is linked to the neurons in the next layer which takes in inputs and gives outputs in the form of weights and biases to the next layer. The intermediate layers between the input and the output layers- *hidden layers* refine these weights and biases to give us an acceptable output. Usually, when an ANN contains more than one hidden layer, it is referred to as a deep neural network. ANNs excel at pattern recognition. The Multi-layer Perceptron is one of the most common ANN used in HEP.

[2]tracks and calorimeter clusters are considered as low-level objects whereas energy, momentum and the identity of the particles are high-level objects

3.1.1 The Multi-layer Perceptron

Initially intended for image recognition, the *Perceptron* gets its name from the human action of perception. Figure 6 shows a perceptron consisting of a single neuron. The input vector $(x1, x2, ..., xn)$ is fed into the neuron with some weights. The neuron then passes a weighted sum of the inputs to the activation function which in turn gives us the output y. If the activation function is g, then the output in this case is given by

$$\boldsymbol{y} = g(W\boldsymbol{x} + \boldsymbol{b})$$

where the matrix W contains the *weights* and the vector $\boldsymbol{b}$ contains the *biases*. The perceptron in figure 6 has not been provided with a bias. The activation function depends on the type of problem. The most common activation function for a regression problem is ReLU (Rectified Linear Unit) and that for a classification problem is Sigmoid.

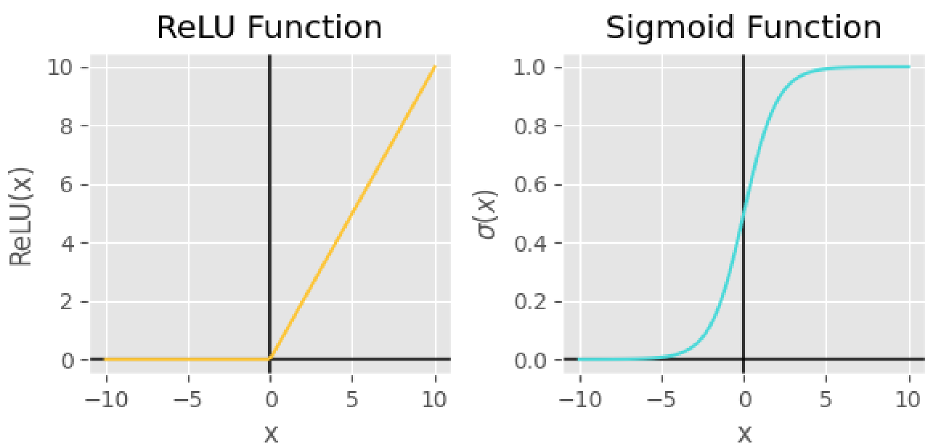


Figure 5: The 2 most common activation functions

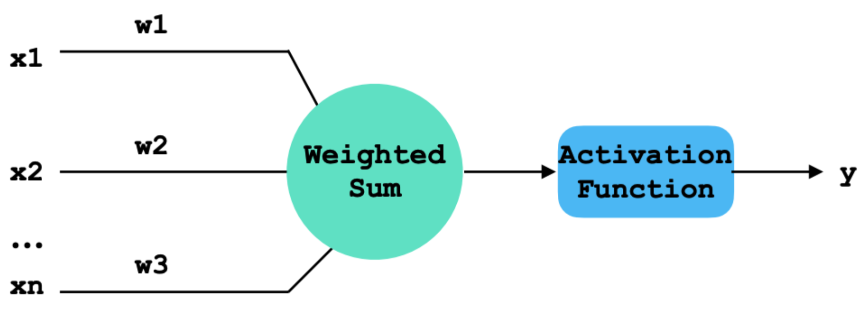


Figure 6: Schematic diagram of a perceptron

One limitation of a single-layer perceptron is that it fails to handle the data when the mapping between the input and output is non-linear [10]. To overcome this limitation we deploy a multi-layer perceptron. A multi-layer perceptron contains a lot of such neurons in a layer and there are at least 2 layers- input and output (see figure 7).

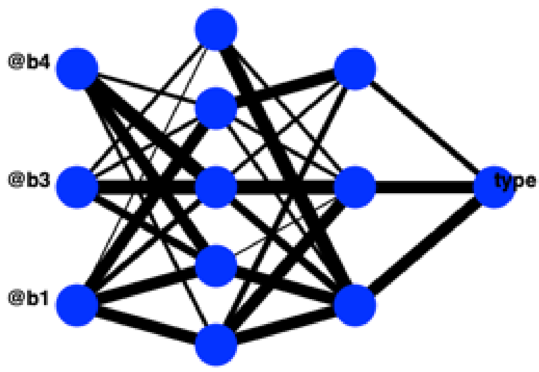


Figure 7: An example of a multi-layer perceptron. The thickness of the lines represents the relative values of the weights.

Given that inputs are combined with initial weights in a weighted sum and are then subjected to the activation function, just like in the Perceptron, the multi-layer perceptron falls under the category of feed-forward algorithms. However, the distinction is that each linear combination is carried over to the following layer. The output of each layer's computation and internal representation of the data is *fed* to the layer below it. This passes through all hidden layers and ends at the output layer.

3.2 Some applications

As mentioned earlier Machine learning is used for track reconstruction, event selection, and jet classification. In a high-dimensional space, neural networks and other ML tools are very commonly used for classification tasks. Since ML tools are very adept at signal and background separation, they have been widely used in the searches for *top quark* and *Higgs boson*[8]. Machine learning will also be used as soft triggers in the upcoming CBM experiment for data reduction. They are also used for anomaly detection to aid in the search for new physics. Machine learning algorithms can be used to improve the accuracy of Monte Carlo simulations, which are used to predict the outcomes of particle collision experiments and compare them with experimental data.

4 Methodologies used

4.1 Data simulation

Two datasets have been used for training the neural network, one containing the muons formed due to ω decay (signal), generated using **PLUTO + UrQMD** and the other containing other muon-like channels (background), generated using UrQMD. The PLUTO thermal model for dimuon signals from the decay of ω mesons is used since UrQMD does not contain any electroweak decays. Both of these inputs are for central **Au+Au** collisions at **8A GeV** energy for the detection of ω mesons.

1. **PLUTO** is a Monte Carlo event generator, which simulates the collision of two heavy ions. It is designed to simulate the full evolution of the collision, from the initial state of the two ions, through the creation and evolution of the quark-gluon plasma, to the final state particles that are detected by the experiment. PLUTO can be highly customised, allowing researchers to include different physics models and adjust simulation parameters to match experimental conditions.

2. **UrQMD** is a classical transport model that uses a semi-classical approach to simulate the evolution of the collision. It simulates the individual interactions of the particles in the collision, tracking their positions, momenta, and interactions over time. It is designed to simulate the entire evolution of the collision, from the initial state of the two ions to the final state particles that are detected by the experiment. It includes a range of physics models, such as hadronic interactions, string fragmentation, and resonances.

Both PLUTO and UrQMD are widely used in the CBM community for simulating heavy-ion collisions and predicting the outcomes of experiments. They are complementary, with PLUTO providing a probabilistic approach that is well-suited to simulating the bulk properties of the quark-gluon plasma, and UrQMD providing a more detailed, particle-level simulation that is better suited to studying individual particle interactions and correlations.

4.2 Data analysis and ANN training

ROOT was used for data analysis as well as for making and training the Multi-layer Perceptron. ROOT is CERN's open-source data analysis framework built on C++. ROOT has very helpful predefined classes which are specially tailored for High Energy Physics problems. It provides a rich set of tools and libraries for data analysis, including statistical analysis, fitting, and plotting. It can handle large datasets efficiently and offers a range of algorithms for data processing. The MLP used is a deep network consisting of 5 layers as shown in figure 8. ROOT's `TMultiLayerPerceptron` class was used to build the network. The input layer is made of inactive neurons and output neurons are linear. The activation function in each neuron in the hidden layer is the Sigmoid function [11], the graph of which is shown in figure 5.

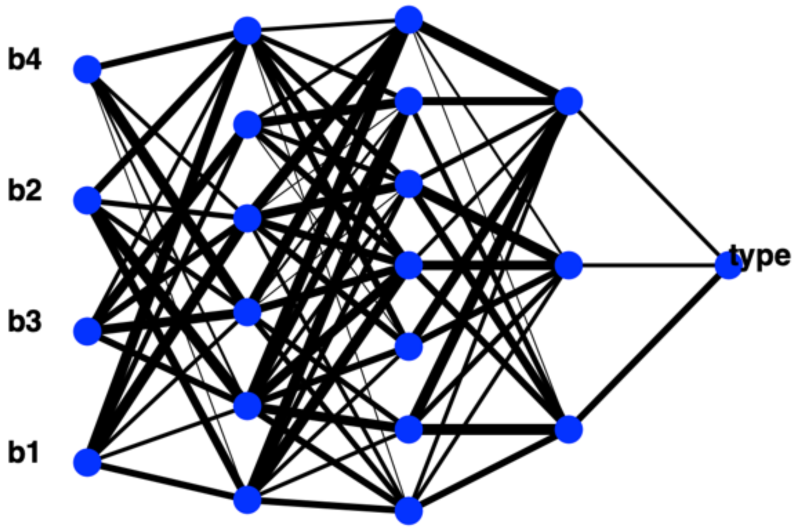
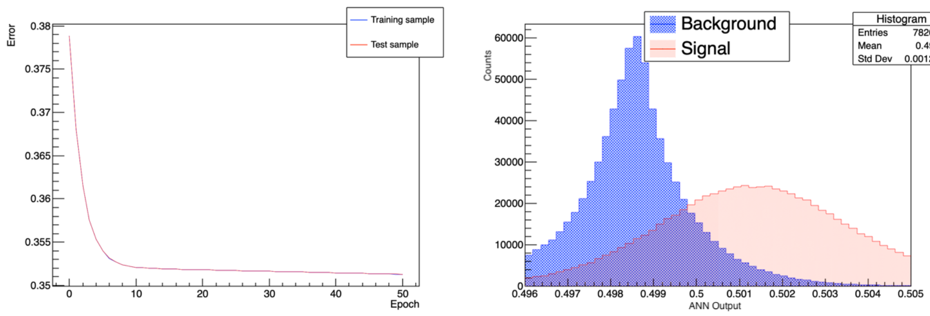


Figure 8: The neural network used in this project

The network shown in figure 8 was tested using 2 simulated Gaussian distributions and it yielded satisfying results as can be seen from figure 9. We see that the training and testing errors have converged and the data is well separable.



(a) Training and testing error

(b) ANN output

Figure 9: Trial results

4.2.1 Analysis of the input variables

After obtaining the simulated CBM data, the signal-to-background ratio obtained was extremely low. Due to this, 30000 signal and background channels each were used to train the model and 14999 have been used to test it. The channels having no hits in the Muon Chamber were omitted as well.

We see in figure 10 that most of the signal (ω-muons) having higher energy was able to pass through more layers of the Muon chamber as compared to the background. As for the STS layers, most of the signal as well as the background have passed. We can see

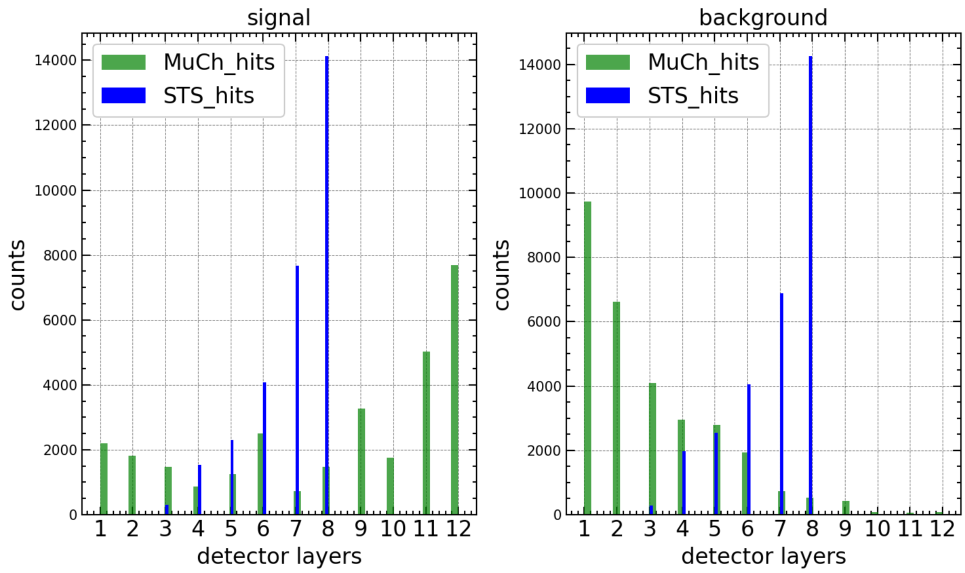


Figure 10: The graph shows the no. of hits recorded in the various detector layers for the signal and background data

that `STS_hits` is not a very useful variable whereas `MuCh_hits` is quite distinguishing.

We can predict the influence of the different features from the correlation map in figure 11. The variable `type` was defined such that the background was assigned 0 and the signal was assigned 1. The magnitude of correlation with `type` is highest for `MuCh_hits` and `chi_MuCh`.

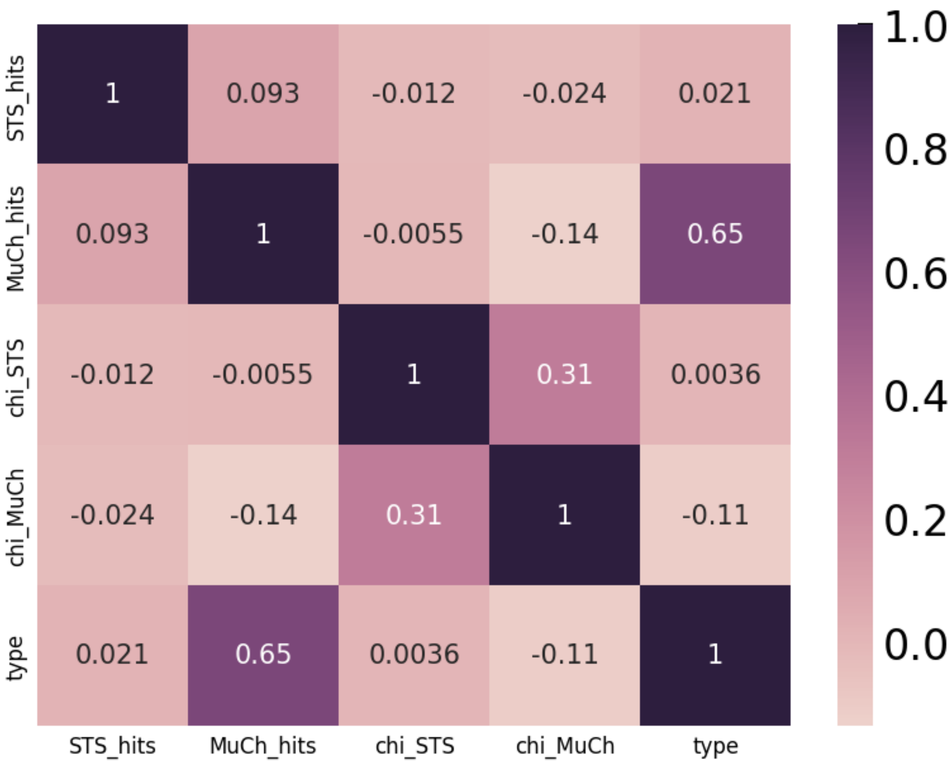


Figure 11: The correlation between different variables
(made using Seaborn)

5 Results and Discussions

We can see from figure 13 that the training and testing errors are overlapping i.e., they have converged. This further validates the credibility of the network for the given data.

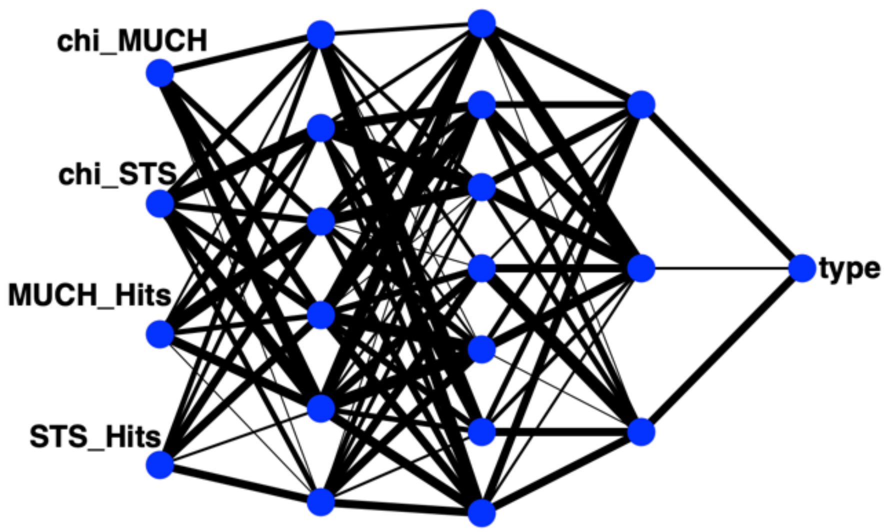


Figure 12: Neural network used for the CBM data

The neural network optimised the 4 input variables to give a single output variable, shown in figure 15, by which we can separate our signal from the background using graphical cuts. Some other architectures of the Multi-Layer Perceptron were used as well but more layers hardly changed the error while training for 100 or more epochs resulted in over-fitting (shown in figure 14). Having one less hidden layer does not cause any problem during the training either but might be helpful when experimental data is supplied which might be a little more complex and the signal-to-background ratio is lower.

Various values for the cuts were tried and their performance is shown in figure 17. We see that we have the best performance around 75%[3]. By placing the cut at 0.4997, we get Efficiency: 76.4518% and Purity: 74.1002%.

Now, this neural network is ready to separate the ω-muons which can be used to calculate the invariant mass of the ω meson.

[3]The performance of the ANN can be further improved by tuning the weights of the network but this was not possible in this thesis due to time constraints.

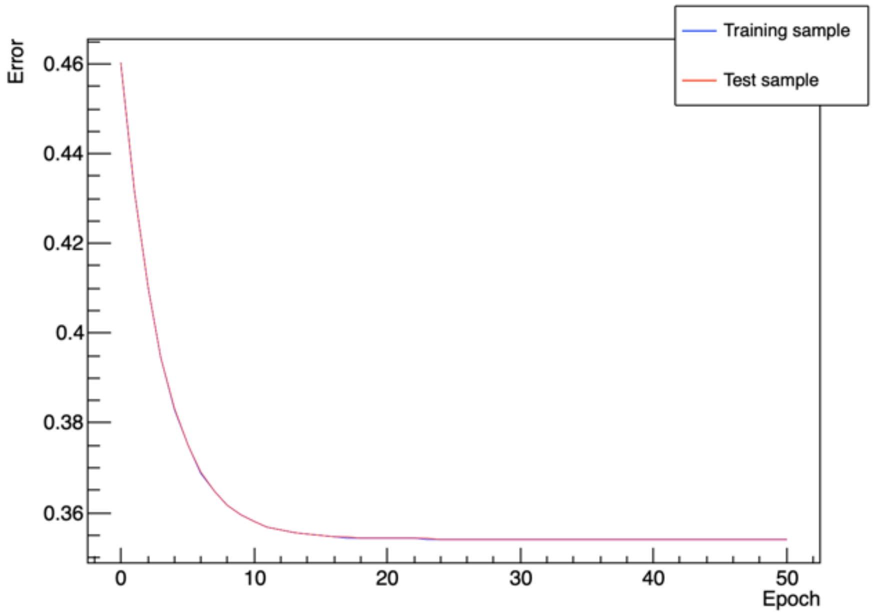


Figure 13: Training and testing error

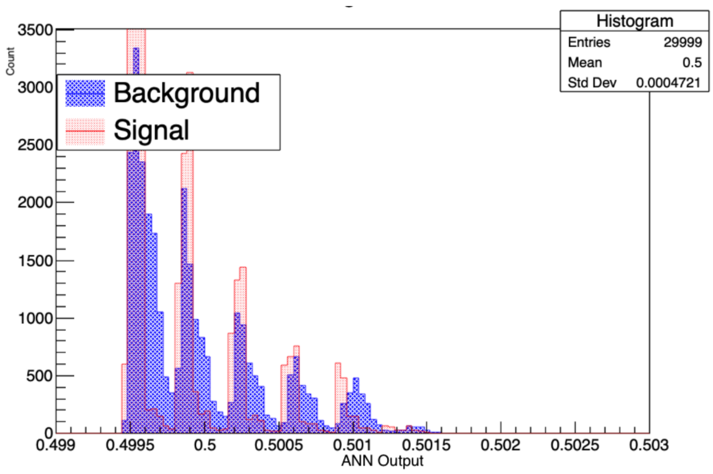


Figure 14: Over-fitting encountered while training for 101 epochs

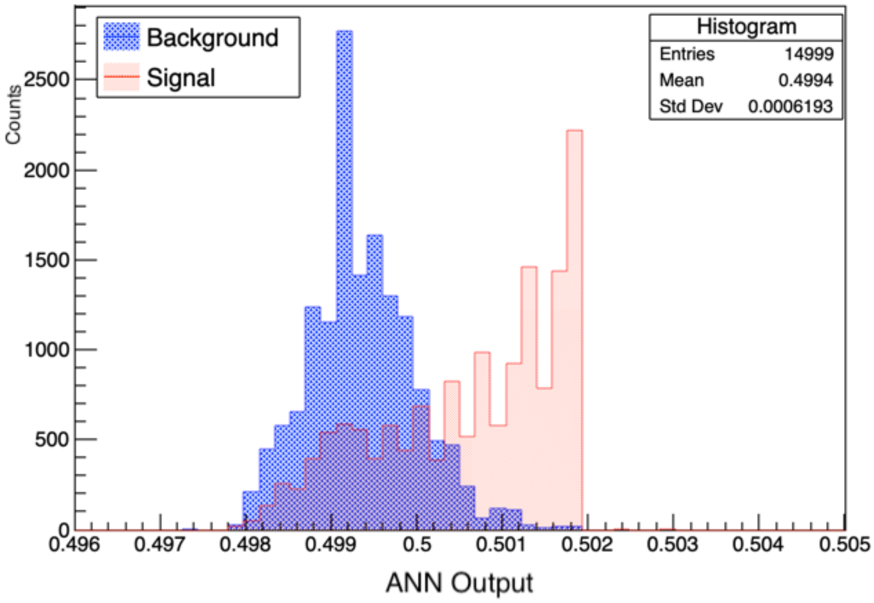


Figure 15: The output of the ANN

```
No. of bg points is 14999
No. of sig points is 14999
Total no. of points is 29998

Cut placed at 0.4997

No. of bg points above cut is 4008
No. of sig points above cut is 11467

Efficiency: 76.4518%
Purity: 74.1002%
```

Figure 16: Result of the optimal cut

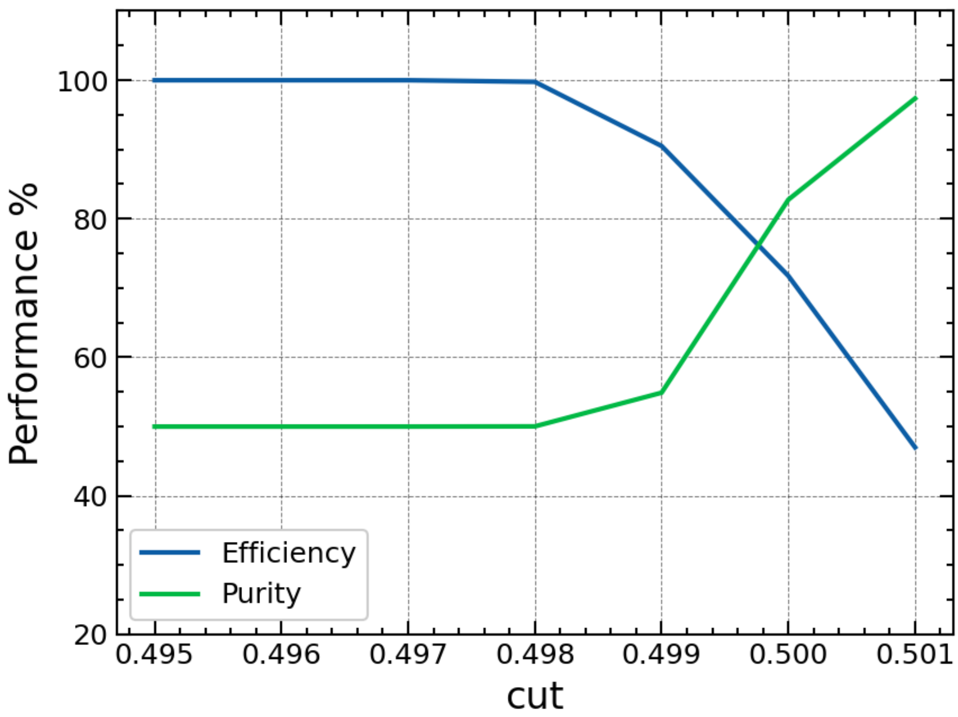


Figure 17: Performance of various cuts

6 Acknowledgement

I can't thank my supervisors, **Dr. Subhankar Ghosh** and **Prof. Subhasis Chattopadhyay** enough. Both of them have left a mark on my life. Their expertise, insights, and feedback have been instrumental in shaping my research and helping me achieve my goals. I feel privileged to have had the opportunity to work with such exceptional scholars and mentors.

Subhankar sir has always encouraged me to study beyond the syllabus and think about what I studied in greater depth. Whenever we meet, he asks some very basic questions regarding the dissertation or what I'm studying, questions which people usually don't pay much attention to but are extremely important. This always kept me on my toes and aided me to study topics in greater detail. His theory classes in college were also quite inspiring because he would dive into the very basics of what he was teaching, Electronics, and connect other areas of physics like Mechanics or Thermodynamics. I can't stress enough how interesting his classes would get. He followed a similar approach even during the dissertation class.

Subhasis sir is the reason I got interested in High Energy Physics in the first place. I attended his seminar on neutrinos back in 2019 at *Vigyan Samagam, Kolkata* and it was so inspiring that I decided to pursue this area of Physics. Ever since then, I wanted to visit VECC. Thanks to **Subhankar sir** and **Subhasis sir** that this dream became a reality. While I was working on my dissertation, **Subhasis sir** always made sure that I enjoyed what I was doing, which is very important. He allowed me to work on one of the upcoming experiments, CBM, which was quite exciting. Working with him on this project has given me a lot of exposure to how things are done in HEP. Not only did he find time from his busy schedule to help me out with my dissertation but also helped me when he had a holiday so that I could complete it on time.

I am greatly indebted to my friend and mentor **Md. Adil Aman**. He was available 24/7 to help me out and enlighten me about various aspects of the CBM experiment. His guidance and suggestions have been immensely helpful in enhancing the quality of my research work. I am grateful for his patience and willingness to share his knowledge and experience with me. I will miss the *adda* over coffee with him and the Grid Room staff at VECC.

I would also like to thank my friend **Abhishek Sharma** for his insights and suggestions on the ML portion of my work. He explained the necessary ML concepts for my dissertation. He is also the person who actually introduced me to ML and showed me some interesting applications. He has always been there for me.

A Appendix

The codes and files required for this project have been uploaded to my GitHub repository:
`https://github.com/raktim711/UG-Dissertation-MLP-CBM`

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