Joint Institute for Nuclear Research

Convolutional Neural Network in application to Slow Magnetic Monopole in the NOvA Experiment.

International Remote Student Training at JINR

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Introduction

Magnetic monopoles, first theorized by physicist Paul Dirac in 1931 [1], are hypothetical particles that carry isolated magnetic charge. Unlike common dipole magnets, which always have north and south poles, magnetic monopoles exist as single poles, either north or south. Their discovery would revolutionize fundamental physics, confirming extensions of Maxwell's equations.

Despite decades of searches, these elusive particles remain undetected. Among the experimental platforms seeking monopoles, the NOvA experiment provides a unique opportunity due to its high segmentation and advanced capabilities for tracking particle interactions.

The NOvA (NuMI Off-Axis Electron Neutrino Appearance) experiment, primarily designed to study neutrino oscillations, consists of two massive segmented liquid scintillator detectors— a near detector close to the source of the neutrino beam and a far detector located 810 km away in northern Minnesota. The far detector's high resolution and sensitivity make it a promising tool for identifying slow-moving magnetic monopoles. Unlike relativistic particles, slow monopoles (with velocities in the range of 10^{-4} to 10^{-2} times the speed of light) interact with matter primarily through ionization, leaving distinct, highly ionizing tracks in the detector.

The current state-of-the-art analysis for monopole detection in the NOvA experiment relies on linear fitting algorithms applied to track reconstructions. These methods, while effective, have limitations when applied to complex and noisy data. The rapid advancements in machine learning, particularly in convolutional neural networks (CNNs), present an exciting opportunity to improve monopole detection by leveraging image-based classification and segmentation techniques.

This project explores the application of convolutional neural networks to improve the detection and identification of slow magnetic monopoles in the NOvA experiment. The work is divided into three primary tasks. Through these tasks, this project not only aims to cross-check and refine the existing monopole analysis but also seeks to demonstrate the potential of deep learning techniques in advancing particle physics.

Abstract

The search for slow-moving magnetic monopoles is a critical endeavor in particle physics, offering insights into the fundamental properties of matter and the universe. This project explores the application of Convolutional Neural Networks (CNNs) in the NOvA experiment to detect and classify slow magnetic monopoles with velocities significantly below the speed of light ($\beta \simeq 10^{-4}$–10^{-2}).

The analysis builds upon existing linear fit techniques while leveraging modern machine learning approaches to improve detection efficiency and accuracy. Three main tasks were undertaken: reproducing linear fit results, performing CNN-based analysis, and calculating efficiency plots to evaluate performance.

This work demonstrates the potential of deep learning in advancing particle identification and supports ongoing efforts in the NOvA experiment to identify exotic particles like magnetic monopoles.

NOvA Experiment

3.1 Overview of the NOvA Experiment

The NOvA experiment is one of the forefront efforts in particle physics aimed at understanding neutrino oscillations, a phenomenon critical to studying the properties of neutrinos and the imbalance between matter and antimatter in the universe. Situated primarily in northern Minnesota and Illinois, the NOvA detectors are designed to capture particle interactions over long baselines using the NuMI beam (Neutrinos at the Main Injector).

The experiment comprises two primary components: the Near Detector, located at Fermilab, and the Far Detector, positioned 810 kilometers away in Ash River, Minnesota. Both detectors are constructed using segmented liquid scintillator cells, which enable precise reconstruction of particle trajectories and energy deposition. This high segmentation and sensitivity make NOvA particularly suitable for studying rare particles, such as slow-moving magnetic monopoles.

The theoretical prediction of magnetic monopoles as carriers of magnetic charge has been a subject of interest since Dirac's proposition in the 1930s. In the context of the NOvA experiment, slow magnetic monopoles are expected to produce distinct ionization tracks due to their low velocities (10^{-4}–10^{-2} times the speed of light) and unique energy loss mechanisms. The Far Detector, with its extensive granularity and large fiducial volume, offers a promising platform for detecting such rare signals.

This project seeks to enhance the analysis pipeline of monopole detection in the NOvA experiment by integrating deep learning techniques. The CNN-based framework enables robust feature extraction from high-resolution image projections of detector data, including charge and time distributions. By addressing the limitations of conventional linear fit algorithms, this work provides a path forward in isolating monopole-like signatures from complex backgrounds.

The outcomes of this study have implications not only for monopole detection but also for broader applications in particle physics, where advanced machine learning techniques are reshaping data analysis methodologies.

3.2 Magnetic Monopoles in Particle Physics

Magnetic monopoles, first theorized by Dirac in 1931, represent one of the most intriguing predictions in theoretical physics. Dirac's work suggested that the existence of a single magnetic monopole could explain the quantization of electric charge, a cornerstone of our understanding of electromagnetism. Monopoles are also generically predicted by Grand Unified Theories (GUTs), which aim to unify the fundamental forces of nature within a single theoretical framework. These theories suggest monopoles could emerge naturally during phase transitions in the early universe. While GUT-scale monopoles are often thought to have extremely high masses ($\sim 10^{17}$–10^{18} GeV), newer theoretical developments have opened the possibility for much lighter monopoles, with masses as low as $\sim 10^{7}$ GeVch for magnetic monopoles has spanned multiple experiments and energy scales, yet no direct evidence for their existence has been found.

Underground experiments have set stringent limits on the flux of slow-moving ($\beta < 0.01$) monopoles, effectively ruling out GUT-scale monopoles at such velocities【7†source】

In this context, the NOvA expevides an exciting new avenue for monopole detection. Its Far Detector (FD) is located on the Earth's surface, where monopoles with masses exceeding $\sim 10^{8}$ GeV can reach without being absorbed by the atmosphere or overburden. NOvA's ability to detect monopoles arises unique energy loss mechanism: ionization. As monopoles traverse the NOvA detector, their energy loss scales with their velocity (β), leaving highly ionizing tracks significantly different from the signatures of minimum ionizing particles like muons.

One crucial factor in understanding monopole detection is their predicted energy deposition, quantified as □□/□□. According to theoretical calculations by Ahlen and Kinoshita , the ionization energy loss of non-catalyzing monopole by:

$$\frac{dE}{dx} = aN_e^{2/3}\left[\ln\left(bN_e^{1/3}\right) - \frac{1}{2}\right]\beta,$$

where N_e is the electron density of the material, and a and b are constants depending on fundamental constants such as the Planck constant, the speed of light, and the monopole's magnetic charge. For NOvA's liquid scintillator, with an electron density of 2.9×10^{23} cm^{-3}.

Theoretical uncertainties remain about the exact value of by factors such as the monopole's charge and potential catalysis of proton decay. While NOvA assumes monopoles carry the Dirac charge and deposit energy solely via ionization, alternative scenarios, like catalyzing proton decay, could lead to higher detection efficiencies or altered track characteristics .

3.3 Relevance of the NOvA Detector for Monopole Detection

The NOvA experime for neutrino oscillation studies, offers unique advantages for magnetic monopole detection due to its detector design and location. The Far Detector (FD) [1], situated near Ash River, Minnesota, is a 14 kton surface-level detector segmented into 896 planes of 384 plastic scintillator cells. Each cell measures 15.5 m × 4 cm × 6 cm, filled with organic liquid scintillator, and alternates between xz and yz orientations, enabling 3D trajectory reconstruction.

Figure 3.1: The Far Detector is located in Ash River, Minnesota. (Credit: Fermilab)

Each scintillator cell contains a loop of wavelength-shifting fiber connected to an Avalanche Photo, which converts scintillation light into electrical signals. These signals are continuously digitized at a 2 MHz rate, allowing the detector to capture high-resolution time and energy information for particle interactions . This fine granularity, combined with the detector's large size, makes it possible to reconstruct long, straight acteristic of monopoles, even in the presence of high cosmic-ray background rates (~130 kHz) .

Monopoles traversing the FD would leave distinct ionization tracks due to their high dE/ dX, which scales linearly lower velocities ($\beta \approx 10^{-3}$), monopoles are expected to have energy deposition comparable to that of minimum ionizing muons, but their prolonged signal duration (up to several microseconds) differentiates them from muons, which cross the detector in nanoseconds. The detector's surface location, while advantageous for accessing monopoles not reachable by underground experiments, also introduces challenges such as distinguishing monopole tracks from the overwhelming cosmic-ray background.

NOvA addresses these challenges through a combination of online triggering algorithms and advanced offline selection methods. The trigger algorithm identifies candidate monopole tracks based on their time and spatial correlations across detector planes, while machine learning techniques, such as Convolutional Neural Networks (CNNs), refine the selection by analyzing the detailed spatial and energy deposition patterns in detector data.

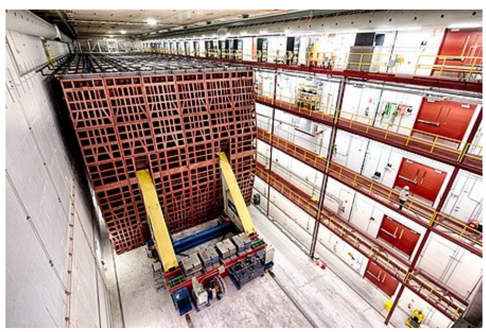

Figure 3.2: Photo of the NOvA Far Detector

Moreover, simulations play a crucial role in optimizing monopole detection. Using tools like Geant4, incorporating both standard particle physics interactions and experiment-specific electronics response. These simulations account for factors such as the detector's reduced sensitivity to slow energy depositions and the impact of noise and calibration uncertainties, ensuring realistic estimates of detection efficiency .

Detector Operation

The NOvA Far Detector (FD) is uniquely positioned for monopole detection due to its surface location, segmentation, and operational capabilities. Unlike conventional underground detectors optimized for neutrino studies, the NOvA FD has the added potential to detect exotic particles like magnetic monopoles.

Design and Structure

The NOvA FD is a segmented liquid scintillator detector comprising 14 kilotons of material. It consists of 896 alternating planes of horizontal and vertical plastic cells filled with organic scintillator liquid. Each cell is equipped with wavelength-shifting optical fibers connected to avalanche photodiodes (APDs), which convert scintillation light into electrical signals. This design allows for high-resolution particle tracking in both the XZ and YZ planes, facilitating the reconstruction of particle trajectories in three dimensions.

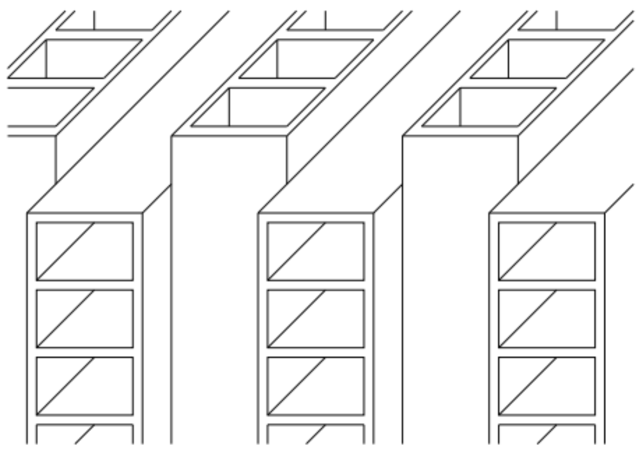

FIG. 1. Schematic of a corner of the NOvA detector. The z direction is to the right, perpendicular to the 15.5 meter-long cells, the ends of which are shown.

Task 1

4.1 Linear Fit Approach for Monopole Detection

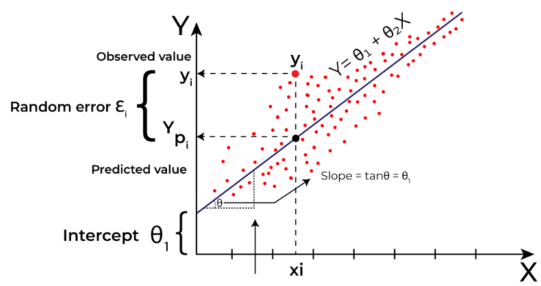

Figure 4.1: Linear Regression illustration

The objective of Task 1 was to reproduce the linear regression results applied to particle trajectories in the NOvA Far Detector, focusing on slow magnetic monopoles. These monopoles are hypothesized particles with a magnetic charge, leaving distinct ionization tracks in the detector. Using a Python-based implementation of linear regression, we aimed to characterize the monopole tracks by extracting slope (“a”) , intercept (“b”), and metrics. This analysis served as a foundational comparison to the “Standard” approach previously applied to monopole simulation data.

4.1.1 Reproducing Linear Fit Results

Methodology

The dataset provided for this task included critical variables: time and charge projections on the XZ and YZ planes, as well as event ID, cell, and plane data. The study focused on comparing the “Standard” and Python-based approaches

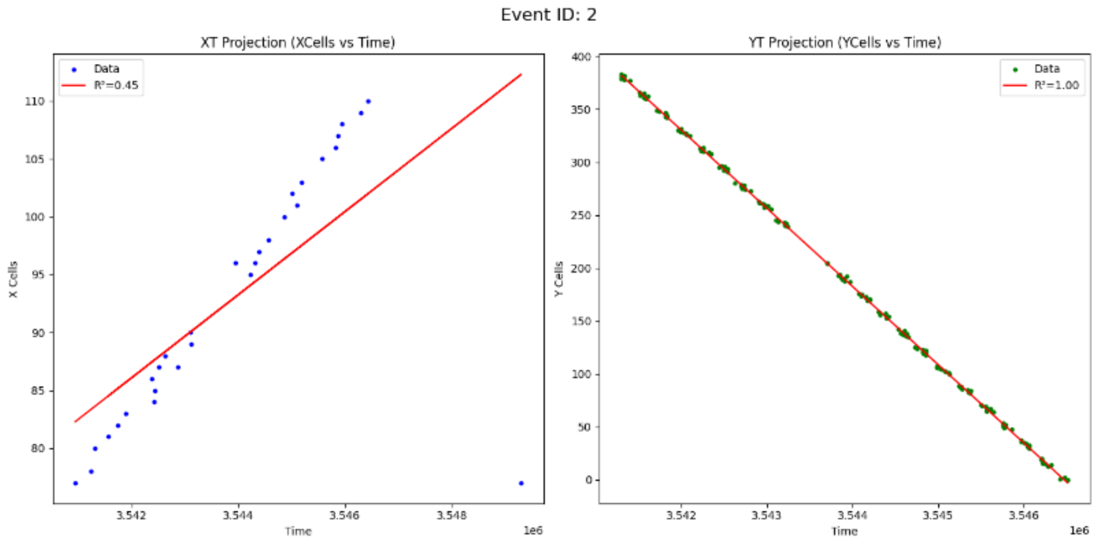

Figure 4.2: Our Result for Event ID 2

to linear fitting, particularly for cases where the Python method demonstrated enhanced performance. The data was divided into XZ and YZ projections for independent analysis. Python's scikit-learn library was used for linear regression, and the methodology consisted of:

1. Splitting the data into XZ and YZ projections.

2. Applying linear regression to each projection to compute the slope, intercept, and values.

3. Comparing Python-generated values with those from the Standard method.

4. Identifying events where the Python method provided better fits compared to the Standard method.

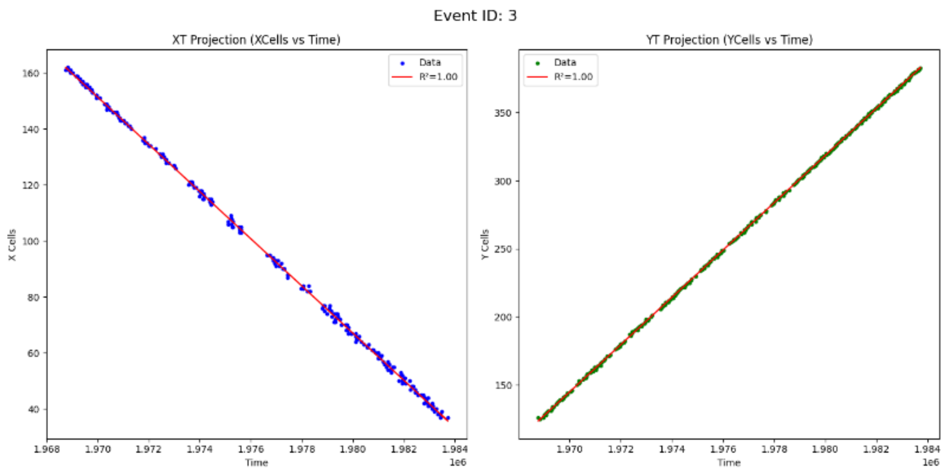

Figure 4.3: Our Result for Event ID 3

Results and Discussion

The Python-based linear regression demonstrated comparable accuracy to the Standard method. Key observations include:

1. Values: Median scores were consistently high (>0.95) for well-fitted tracks in both XZ and YZ projections.

2. Enhanced Identification: Several events showed higher scores in Python's implementation, highlighting its robustness in identifying linear tracks.

Figures 4.2 and 4.3 illustrate the comparison of scores between the two methods

Conclusion

This task successfully demonstrated the applicability of Python-based linear regression for analyzing monopole tracks in the NOvA Far Detector. The results validated its consistency with the Standard approach while revealing its potential for improved monopole detection in challenging cases.

Task 2

5.1 Comparative Analysis of R^2 Metrics

5.1.1 Introduction

The second task extended the linear regression analysis by focusing on comparing the R^2 metrics between the Python and Standard approaches for monopole trajectory fits. The aim was to identify and analyze cases where Python outperformed the Standard method, specifically when Python achieved an $R^2 \geq 0.95$ while Standard did not.

5.1.2 Methodology

The steps undertaken in this task included:
1. Calculating the minimum R^2 values across XZ and YZ projections for both Python and Standard methods.

2. Identifying events where the Python approach satisfied the condition $\ell\min(R^2\_XT, R^2\_YT)\ell \geq 0.95$ while the Standard method failed.

3. Plotting the differences in R^2 values for identified cases and visualizing the corresponding events.

5.1.3 Results and Discussion

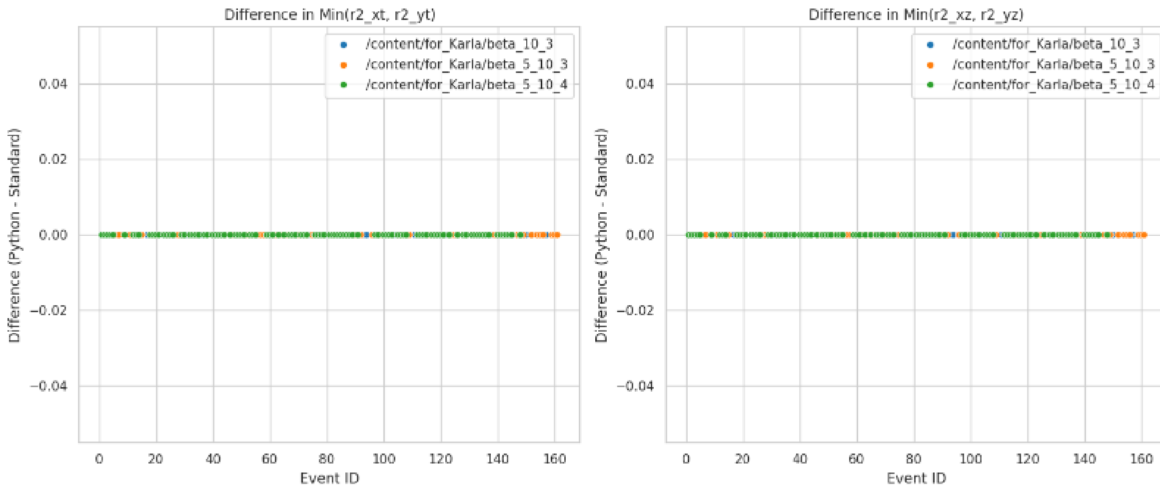

Figure 5.1 presents histograms of differences

The analysis revealed no events where the Python approach succeeded while the Standard method failed. Specifically:

- The minimum R^2 values for both methods were identical across all events.
- No significant differences in R^2 metrics were observed, as illustrated in Figure 5.1.

This outcome underscores the equivalence of the two approaches in detecting monopole-like tracks, with Python providing results consistent with the Standard method.

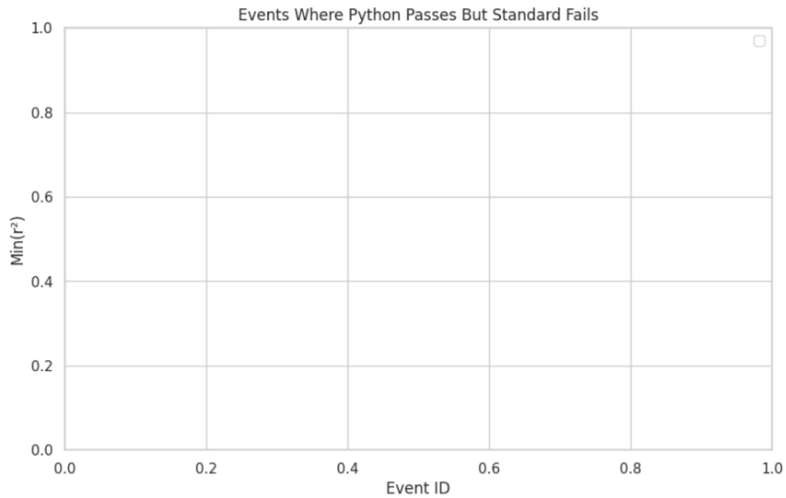

Figure 5.2: Events where python passes but standard fails.

Note: No events were found where Python passes but Standard fails.

Conclusion

The comparative analysis confirmed that the Python linear regression algorithm performs on par with the Standard approach. The lack of discrepant events reinforces the validity of the Python implementation for monopole trajectory analysis.

Task 3

Convolutional Neural Network (CNN) Analysis

The third task focused on using convolutional neural networks (CNNs) [4] to analyze and classify particle interactions in the NOvA Far Detector. The objective was to leverage the CNN's ability to distinguish monopole events from background activity using 2D projections of time and charge data. Unlike linear regression, this approach sought to automate the identification of complex features in the detector data, making it particularly suitable for handling large datasets and mixed-event overlays.

Methodology

Dataset Preparation

The dataset comprised several categories of images:

1. Beta (monopoles): Simulated monopoles with varying velocities.

2. Muon (background): Representing cosmic-ray muons.

3. Snews (background): Representing normal NOvA far detector activity over 5 ms.

4. Overlay (test): A mix of monopoles and background events.

Images were divided into time and charge projections, resized to 256x256 pixels, and normalized. Time images were scaled by 65535, while charge images were scaled by 255 . The dataset was split into training (70%), validation (20%), and test (10%) subsets, ensuring balanced representation

CNN Architecture

The CNN model adopted a U-Net structure with encoder-decoder architecture.
Key features included:

- Encoder: Successive convolutional and max-pooling layers to extract spatial features.
- Decoder: Transposed convolutions for up-sampling and segmentation.
- Output Layer: Sigmoid activation for binary classification.

Training and Evaluation

The model was trained using binary cross-entropy loss and the Adam optimizer. A batch size of 16 and 10 epochs were used. Performance was evaluated using accuracy and Intersection over Union (IoU) metrics.

Results and Discussion

Performance on Validation and Test Sets

The CNN achieved:

- Validation Accuracy: 83.16%.
- Test Accuracy: 88.25%.

These metrics highlight the model's capability to classify monopole and background events effectively.

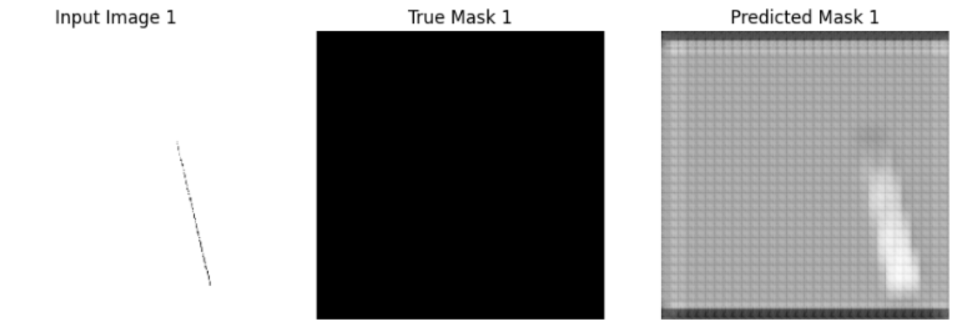

Figure 6.1

Figure 6.2

Figure 6.3

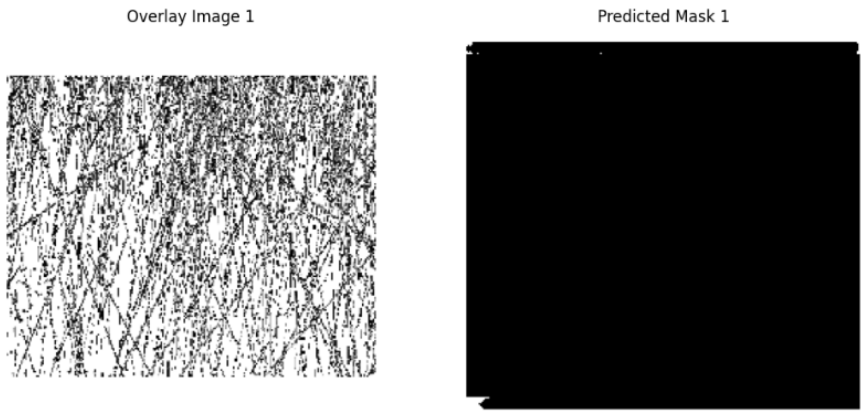

Figure 6.4

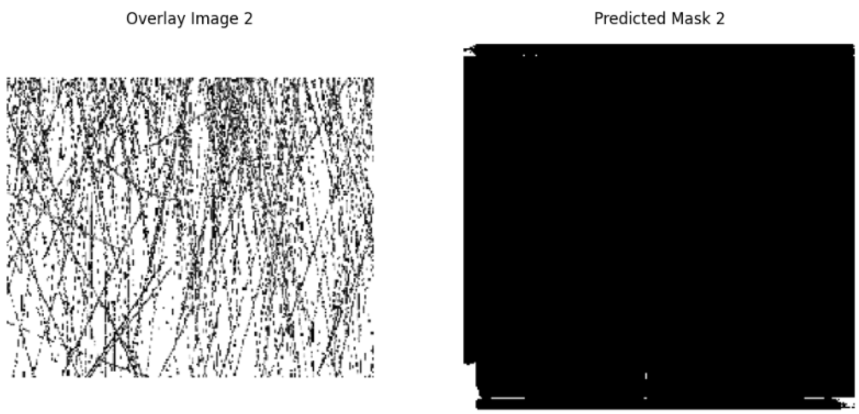

Figure 6.5

Importance of the Task

This task underscores the importance of advanced machine learning techniques in high-energy physics. CNNs offer a scalable and automated approach to analyzing complex datasets, complementing traditional methods like linear regression. The ability to segment and classify monopoles from noisy backgrounds is crucial for improving detection efficiency and broadening the scope of monopole searches.

Aknowledgment

The successful completion of this project would not have been possible without the invaluable guidance and support of Dr. Oleg Samoylov. His expertise in particle physics and deep understanding of the NOvA experiment provided a crucial foundation for this research. His willingness to share his knowledge and provide insights throughout the process proved instrumental in navigating the complexities of the tasks.

I am deeply grateful for Dr. Samoylov's patient mentorship, constructive critiques, and unwavering encouragement, which have been a source of inspiration throughout this journey. This work stands as a testament to his dedication to fostering student growth and his commitment to advancing scientific understanding in the search for magnetic monopoles.

Bibliography

[1] M. A. Acero, et al., "Search for Slow Magnetic Monopoles with the NOvA Detector on the Surface," Phys. Rev. D 103, 1 (2021).

[2] M. A. Acero et al., "Improved measurement of neutrino oscillation parameters by the NOvA ex- periment," Phys. Rev. D, vol. 106, no. 3, p. 032004, 2022.

[3] M. J. Frank, A. Antoshkin, D. Coveyou, E. C. Dukes, R. Ehrlich, and L. Panda, "Latest Magnetic Monopole Search Results from NOvA," PoS, vol. EPS-HEP2023, p. 441, 2024.

[4] A. Aurisano, A. Radovic, D. Rocco, A. Himmel, M. D. Messier, E. Niner, G. Pawloski, F. Psihas, A. Sousa, and P. Vahle, "A Convolutional Neural Network Neutrino Event Classifier," JINST, vol. 11, no. 09, p. P09001, 2016.