Machine Learning Applied to Multi-Electron Events in Scintillator

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Objective

This project attempts to use **supervised machine learning algorithms** as a means to distinguish between one and two electron events and predict the electron(s) corresponding initial position(s) in a scintillator.

Introduction

The classical picture of spherical nuclei is far from the reality of the true nuclear structure. **Shape coexistence is a nuclear phenomenon, where the nucleus exists in two stable shapes at the same excitation energy** [1]. Nuclear properties provide unique information on the impetuses that foster changes to the nuclear structure of rare isotopes. In some neutron-rich nuclei, 0^+ states are predicted to exhibit shape coexistence. Therefore they are compelling to study, **but experimentally challenging** [2]. At low energies, where the only energetically allowed decay mode is $0^+ \rightarrow 0^+$, conversion electron spectroscopy is the only viable technique to probe their properties.

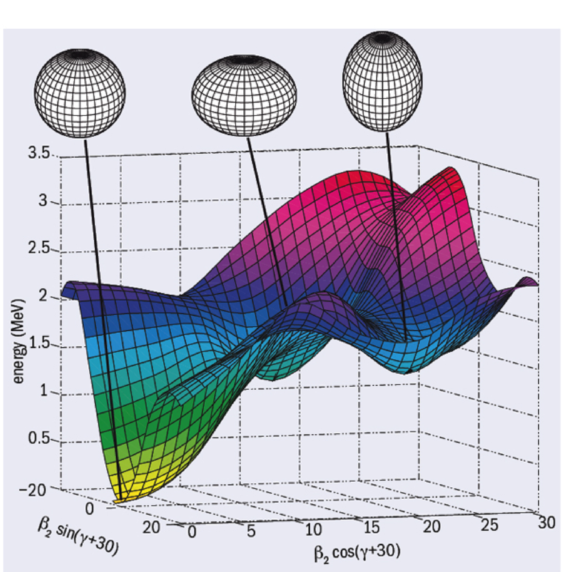

Figure 1: ^{186}Pb exhibits shape coexistence [3].

Sean Liddick's group employs conversion electron spectroscopy to study these transition rates. When a neutron-rich nucleus beta decays, a neutron transforms into a proton and emits an electron (β). The excited nucleus can then interact electromagnetically with the surrounding orbital electrons. This can result in the ejection of an internal conversion electron (e^-) from the atom [4]. **Because this process is essentially simultaneous in time, it is pivotal to differentiate between the electron (β) emitted from the nucleus and the internal conversion electron (e^-) emitted from the atom.**

Electron Events

Given the energy deposited in each pixel of the scintillator, we want to **classify** electron events and **predict** the origin of the electron(s).

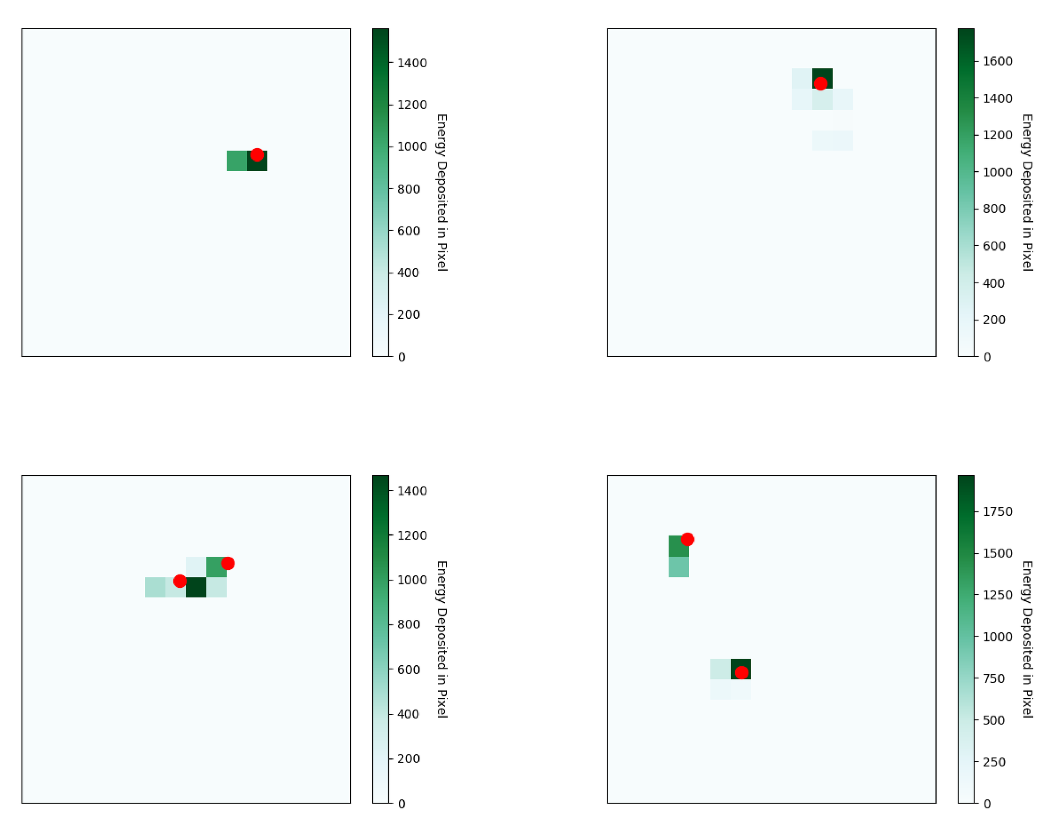

Figure 2: Scintillator events from simulated dataset. The upper left and right are one electron events. The lower left and right are two electron events. Red dots indicate the starting positions of the electrons inside of the scintillator.

Convolutional Neural Network

We developed two convolutional neural network architectures in Keras to (i) classify one and two electron events and (ii) predict the origin of the electron for one electron events. We then trained the CNNs on simulated datasets.

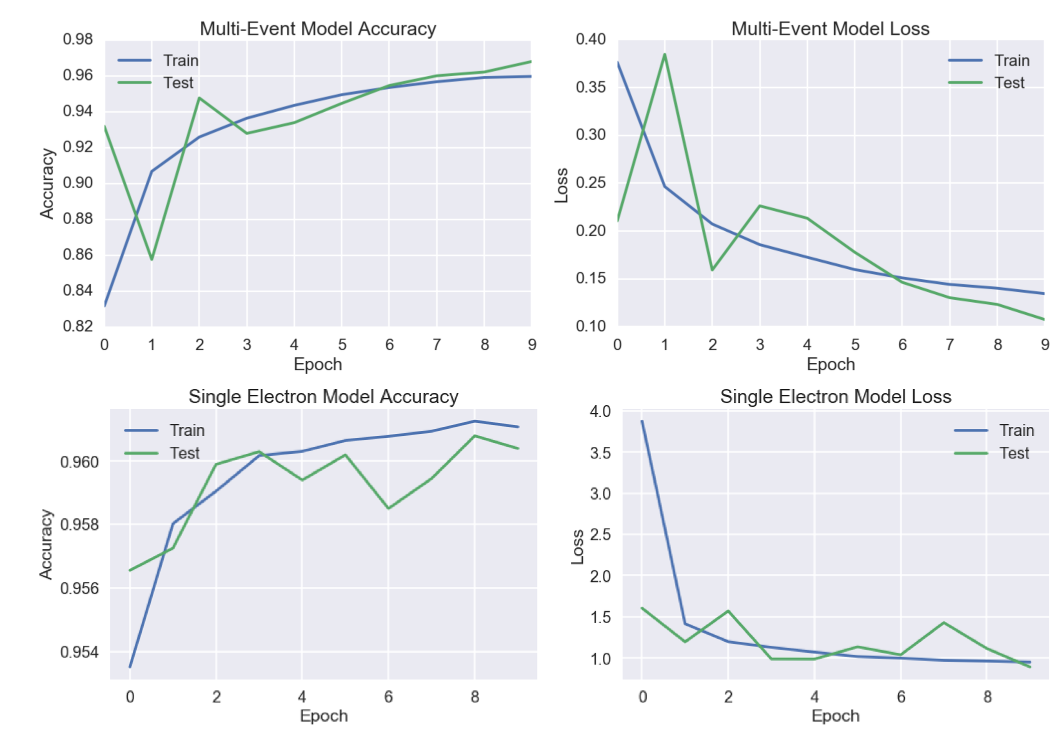

Figure 3: Top: Multi-Event Model classifies events as one or two electrons. Bottom: Single-Electron Model predicts (x_0, y_0) of the electron in single electron events.

Results

- **Multi-Event Model was successful** at categorizing one and two electron events with **96.79 % accuracy.**
- Single-Electron Model, on average, predicted positions 1.15 mm away from the actual position, which is within the width of one pixel (3mm). Randomly guessing a point inside of the pixel produced a mean error of 1.567 mm. However, **77 % of our model's error were less than 1.567 mm.**

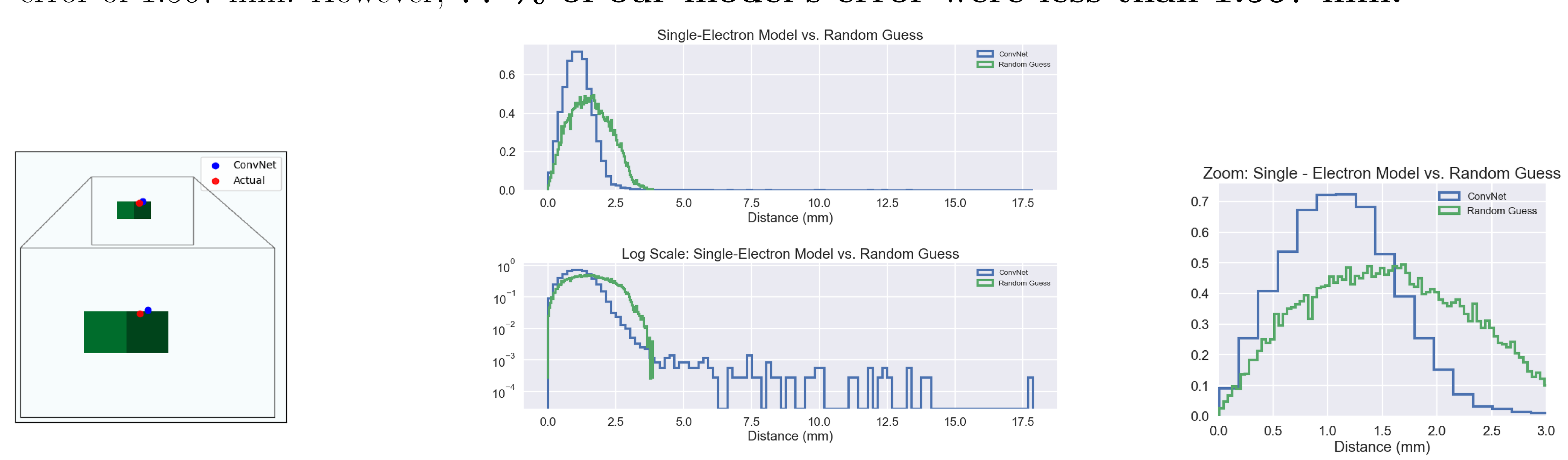

Figure 4: Left: Blue is the predicted position of the electron by the CNN, red is the actual position of the electron. Middle: Histograms of the distances between our predicted position and the actual position of the electrons. Right: Restricting the x-axis on top middle plot.

Conclusion

With the **implementation of machine learning techniques, we were able to successfully train a convolutional neural network (CNN) to distinguish between a one and two electron event. Furthermore, we successfully trained a CNN to predict the origin of the electron for one electron events.** Relative to the size of a pixel, our model's mean error was marginally better than that of the random guessing algorithm's, therefore a proper uncertainty quantification needs to be explored. This technique will be generalized to predict the origins of the electrons in the multi-event case and their respective initial energies. These models were trained and tested on simulated data provided by Sean Liddick, so they will need to be tested with a noisy dataset. Once these models are completely generalized, they can then be applied to real experimental data. If they perform well on the experimental data, then **machine learning will be a viable data analysis technique for the Sean Liddick group and conversion electron spectroscopy in general.**

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