# Machine Learning Applied to Multi-Electron Events in Scintillator

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**Abstract.** Conversion electron spectroscopy is a viable tool when studying the nuclear phenomenon, shape coexistence. When a neutron-rich nucleus beta decays, a neutron transforms into a proton and emits an electron ($\beta$). The excited nucleus can then interact electromagnetically with the surrounding orbital electrons. This can result in the ejection of an electron ($e^-$) from the atom, a process called internal conversion. Because this process is essentially simultaneous in time, it is pivotal to differentiate between the electron ($\beta$) emitted from the nucleus and the internal conversion electron ($e^-$) emitted from the atom. Here we apply supervised machine learning algorithms to distinguish between one and two electron events, as well as determine the origin of the electron. We used two different convolutional neural network (CNN) architectures to accomplish these tasks. With simulated data, we were able to successfully train a CNN to distinguish between a one and two electron event with 96.79% accuracy. Furthermore, we successfully trained a CNN to predict the origin of the electron for one electron events. Our results show promise that our models' performance will generalize to experimental data. Once our models are complete, machine learning will be an important data analysis tool for conversion electron spectroscopy.
Keywords: Nuclear shape coexistance, Machine learning, Neural networks.

## 1. 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, such as shape coexistence, are expected to vary significantly as a function of proton and neutron number (Z,N). Their 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 (see Fig. 1). Therefore they are compelling to study, but experimentally challenging. 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. These shape-coexisting states are paramount in understanding changes to the nuclear structure of exotic nuclei (see below for further discussion) [2].

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Radioactive nuclei are produced and isolated at the National Superconducting Cyclotron Laboratory (NSCL) at Michigan State University. Sean Liddick's group focuses on characterizing transition rates of ground and excited states in nuclei as a function of proton and neutron number. The decay transition rates of the excited states can provide quintessential information of the coexisting structures. 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 ($\beta$). 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 [3]. Because this process is essentially simultaneous in time, it is pivotal to differentiate between the electron ($\beta$) emitted from the nucleus and the internal conversion electron ($e^-$) emitted from the atom.

Machine learning may offer a means to a solution for this problem. A sub-field of artificial intelligence, machine learning is becoming ubiquitous in all fields of science. Due to the current information revolution, there has been an exponential increase in computational power. With this ability to effectively and efficiently apply new techniques to large datasets, machine learning has been blossoming [4]. Many researchers are finding it advantageous to employ these techniques to their own data analysis. Sean Liddick's group records a substantial amount of data making their experiment a potential candidate for machine learning techniques. In this paper, we attempt to use supervised machine learning techniques as a means to distinguish between one ($e^-$) and two ($\beta$, $e^-$) electron events and predict the electron's initial positions based on the energy depositions in a scintillator.

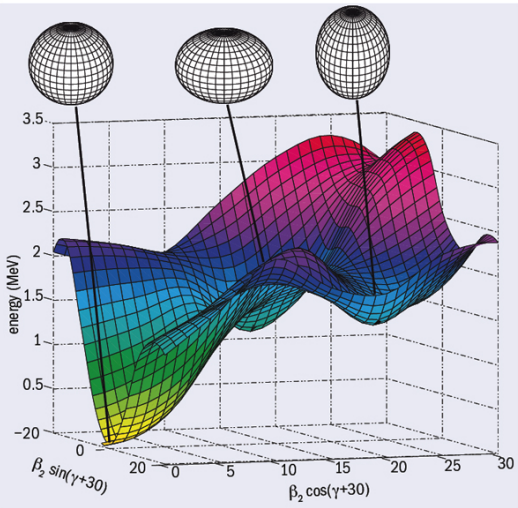


**Figure 1.** Shape coexistence is a nuclear phenomenon can have nuclei exist in variety of shapes at similar energies. An example of this is $^{186}$Pb [5].

## 2. ELECTRON EVENTS

In this experiment, a scintillator with dimensions 4.8 cm $\times$ 4.8 cm $\times$ 0.3 cm is divided into a 16 $\times$ 16 grid, with a total of 256 grid sites. Each grid site or pixel on the detector is 3 mm $\times$ 3 mm. For a given event, the energy deposited in each pixel is recorded.

The data sets that we are using to implement our machine learning techniques were simulated by Sean Liddick. The simulation consists of a detector that is a single crystal of $CeBr_3$. Two different data sets were created. For the first simulated data set, the source was a single 3.06 MeV electron emitted isotropically with a starting position distributed uniformly throughout a rectangular volume of size 3 cm $\times$ 3 cm $\times$ 0.3 cm centered on the detector itself. For the second data set, the source was two 3.06 MeV electrons emitted independently in the same isotropic manner as the single electron case. Note that this simulation does not consider the simultaneous emission of these two electrons. During the electron scattering process, it is possible for the electron(s) to deposit energy in multiple locations, however these locations will always be contiguous. It is important to note that the simulation contains no light emission and no energy resolution. Figure 2 is a visual representation of the two different types of electron events.

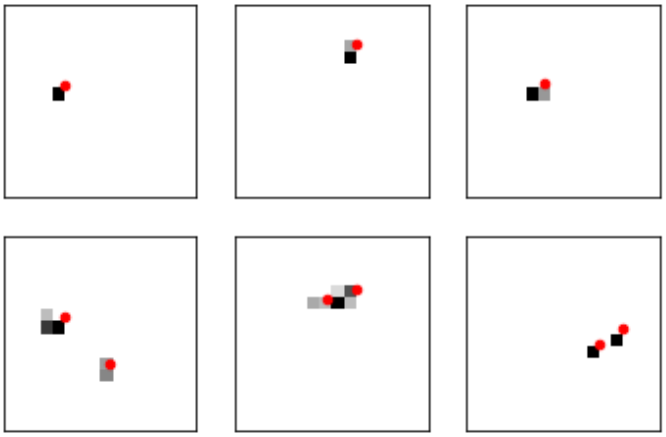

**Figure 2.** Top: One electron events. Bottom: Two electron events. Red dots indicate the starting position(s) of the electron(s).

The goal is to implement machine learning techniques to distinguish between a one electron event, where there is a single contiguous interaction site and a two electron event, where there can be multiple contiguous interaction sites or a larger contiguous interaction site compared to the single electron case. In addition, we will identify the initial position $(x_0, y_0)$ of the electron(s) for an event.

## 3. CONVULATIONAL NEURAL NETWORK

We chose to use convolutional neural networks as a means to perform our desired tasks. Convolutional neural networks (CNN) are a class of deep neural networks optimized for analyzing images. CNNs provide the computer with the ability to see. This will allow us to treat each scintillator event as a visual image, so the computer can see the electron's interaction sites on the scintillator. For a detailed explanation on convoluational neural networks and other machine learning techniques, see [4]. The source code for these two CNNs are located at this link.

### 3.1 *Single-Electron Model*

We created a CNN architecture in Keras[1] to predict the origin of the electron in single-electron events. We first created two mutually exclusive sets from the single-electron data set. Our training set consisted of 333,333 events and our testing set consisted of 20,000 events. Our CNN architecture consisted of one two-dimensional convolutional layer, where the output from this layer was then flattened into a one dimensional array and connected to a feed forward neural network layer with 512 nodes. This layer was connected to the output layer with two nodes, which are representative of the $x$ and $y$ positions of the electron. We used the following loss function

$$\text{MSE} = \frac{1}{N}\sum_{i=0}^{N-1}(\hat{y}_i - y_i)^2. \tag{1}$$

Figure 3 shows the model's performance throughout the duration of the training. After training the model for ten epochs, we achieved a model accuracy of 96%.

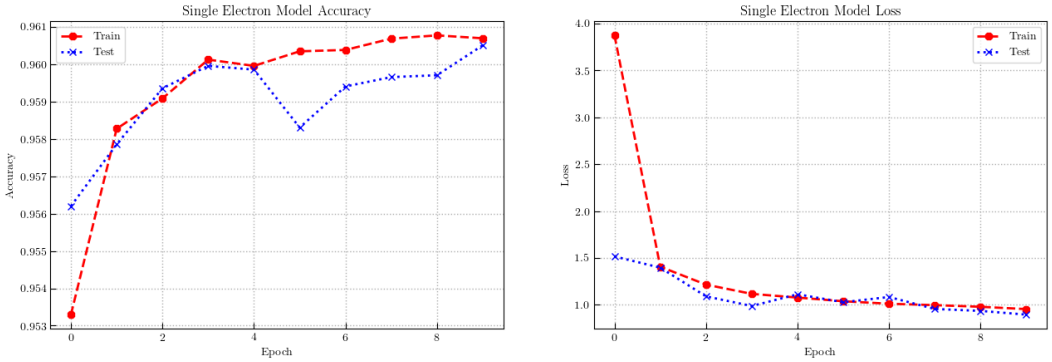


**Figure 3.** Single-Electron Model was trained for ten epochs. Left: Model's accuracy after each epoch. Right: Model's loss after each epoch.

[1] https://keras.io

### 3.2 *Multi-Electron Model*

The second CNN architecture was designed to correctly categorize a one and two-electron event. Firstly, we created a new data set that contained both one and two-electron events. This was done by randomly selecting events from each data set until our new data set had size 200,000. We then trained the CNN on 150,000 events and tested on the remaining 50,000 events.

Our CNN architecture consisted of two two-dimensional convolutional layers that were then connected to a two-dimensional max pooling layer. This was then connected to a single neural network layer with 128 nodes. Finally, this was connected to the output layer, which was another neural network layer with two nodes, where one node represents the probability of the event being a one-electron event and the other represents the probability of a two-electron event. We used the categorical cross entropy loss function for training our model. This loss function has the form

$$H(y) = -\sum_i y_i \log(\hat{y}_i), \tag{2}$$

where $\hat{y}_i$ is the predicted probability of the event being class $i$ and $y_i$ is the true probability of the event bein class $i$.

## 4. RESULTS

### 4.1 *Single Electron Model*

The Single-Electron Model was designed to predict the origins of the electron in one-electron events. After training, our model was 96% accurate on the testing set. When evaluating the distances between the predicted value $(\hat{x}, \hat{y})$ and the actual value $(x_0, y_0)$, we found that on average our model predicted points about 1.2 mm away from the actual origin. This is promising considering the width of a pixel totals in 3 mm, so the majority of the time we are predicting points that are within the same pixel. However, to further benchmark the performance of our model, we compared it with a random guessing algorithm. Using the assumption that the electron starts in the pixel with the highest energy (which is correct 70% of the time), the algorithm was written to randomly pick a point within that pixel. Figure 4 shows a comparison of the CNN predictions to the random guessing algorithm predictions. The histogram plots show the distance between the predicted ($\hat{x}$, $\hat{y}$) and the actual ($x$, $y$) on the x-axis and then the frequency of these distances on the y-axis.

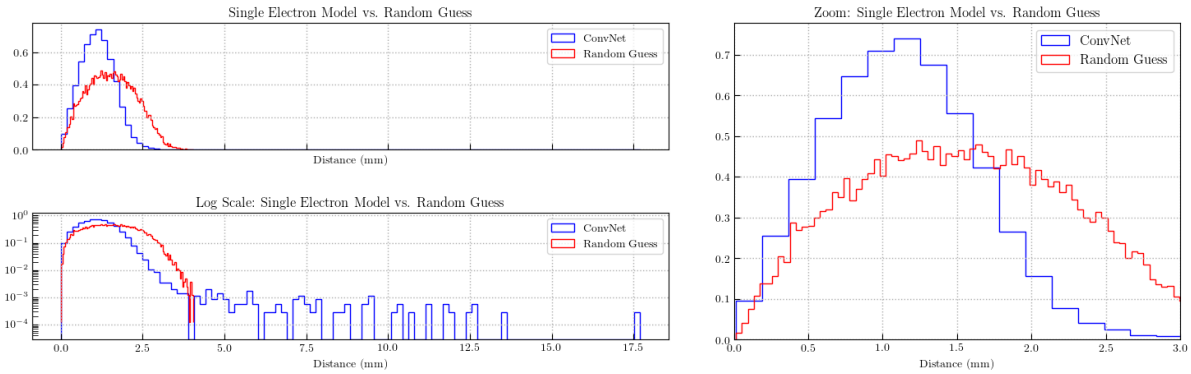


**Figure 4.** On the left are two plots representing the Single-Electron Model's predictive error versus the error of the random guessing algorithm. On the right limits the x-axis to [0,3].

On average, the random guessing algorithm predicted points that were 1.5 mm away from the actual point. Our model's error was less than the random guessing algorithm's on average 77% of the time. This means our model's performance is better the majority of the time than randomly guessing. However, our neural network's prediction is still only marginally better than the random guess. Therefore, it is necessary to define a proper uncertainty quantification and resolution scale so that a true benchmark for our neural network's performance can be conducted. Table 1 contains more metrics from the Single-Electron Model's performance and the random guessing algorithm's performance. The table includes the average distance between the actual origin and the predicted origin of the electron, the closest prediction to the actual origin of electron, the furthest prediction from the actual origin of electron, and the $90^{th}$, $95^{th}$, $99^{th}$ percentiles. The percentiles show that 90%, 95%, and 99% of our predictions were 1.9 mm, 2.165 mm, and 3.293 mm from the actual origin of the electrons, respectively.

**Table 1.** Metrics for Single-Electron Model and Random Guessing Algorithm (mm)

| **Method** | **Average** | **Min** | **Max** | **90 %** | **95 %** | **99 %** |
|---|---|---|---|---|---|---|
| Single Electron Model | 1.2117 | 0.011 | 21.253 | 1.900 | 2.165 | 3.293 |
| Random Guessing | 1.555 | 0.008 | 3.944 | 2.574 | 2.805 | 3.218 |

### 4.2 *Multi-Electron Model*

The Multi-Electron Model was designed to distinguish between a one-electron and two-electron event given only the scintillator with the amount of energy deposited in each pixel. After training, our model achieved a 96.79% accuracy (see Figure 5). This means the model was able to successfully distinguish the difference between the simulated one and two-electron events. This result

shows promise of our CNN model's generalizability to real experimental data.

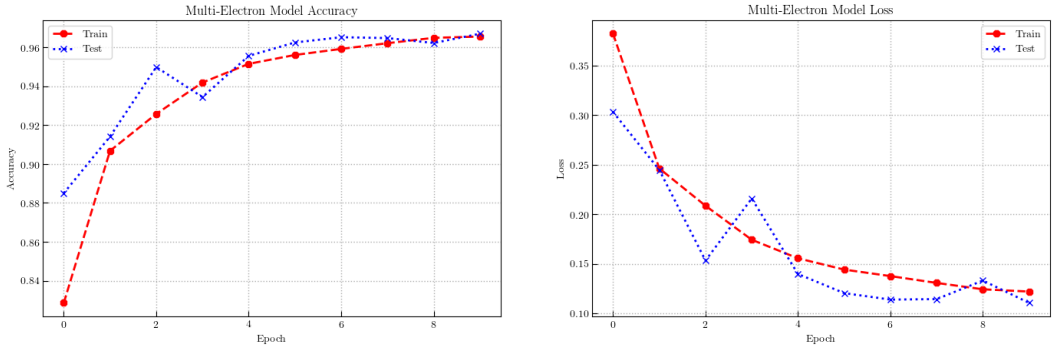


**Figure 5.** The Multi-Electron model was trained for ten epochs. Left: Model's accuracy of the model after each epoch. Right: Model's loss of the model after each epoch.

## 5. CONCLUSION

With the implementation of machine learning techniques, we were able to successfully train a 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 two-electron 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 data set with light emission and an energy resolution. 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.

## 6. ACKNOWLEDGMENTS

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## References

[1] R. Lucas. Nuclear shapes. Europhys. News, (2001)

[2] A. Gade and S.N. Liddick. Journal of Physics G: Nuclear and Particle Physics, 43(2), 1 (2016)

[3] O. Dragoun. Internal Conversion-Electron Spectroscopy. *Advances in Electronics and Electron Physics*, Vol 60. Academic Press, 1983. doi:https://doi.org/10.1016/S0065-2539(08)60888-4. URL http://www.sciencedirect.com/science/article/pii/S0065253908608884

[4] P. Mehta, M. Bukov, C. H. Wang, A. G. R. Day, C. Richardson, C. K. Fisher and D. J. Schwab. ArXiv: 1803.08823.

[5] Andrei Andreyev and K U Leuven and Jürgen Kluge. *Exotic lead nuclei get into shape at ISOLDE* CERN Courier, 19 Sept 2007