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Identification of light leptons and pions in the electromagnetic calorimeter of Belle II

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ABSTRACT

The paper discusses new method for electron/pion and muon/pion separation in the Belle II detector at transverse momenta below 0.7 GeV/c, which is essential for efficient measurements of semi-leptonic decays of B mesons with tau lepton in the final state. The method is based on the analysis of patterns in the electromagnetic calorimeter by using a Convolutional Neural Network (CNN).

1. Introduction

Searches for New Physics at the intensity frontier are based on very precise measurements of rare processes within the Standard Model. Of particular interest, because of persistent hints of Lepton Flavour Universality (LFU) violation, are semi-leptonic decays of B mesons, e.g. decays mediated by the $b \to c\tau^+\nu_\tau$ transitions with a tau lepton in the final state and decays involving $b \to s\mu^+\mu^-$ and $b \to se^+e^-$ transitions. In decays with tau lepton in the final state, the tau lepton must be reconstructed from its long-lived decay products, for example from the decays $\tau^- \to \mu^-\bar{\nu}_\mu\nu_\tau$ or $\tau^- \to e^-\bar{\nu}_e\nu_\tau$. In the Belle II experiment [1,2], the momentum spectrum of light leptons from tau decays is rather soft, a sizable fraction being below 0.7 GeV/c. One of the crucial steps in the analysis of these decays is identifying low momenta light leptons (e or μ) from hadronic background (mostly π). The simplest baseline feature for separating electrons from other charged particles (muons and pions) is E/p, the ratio between the energy measured in the electromagnetic calorimeter and the reconstructed momentum of a topologically matched charged track. This variable provides an excellent separation for particles with $p > 1$ GeV/c, but due to increased energy losses from bremsstrahlung for low momentum electrons, the separation is less distinct [3]. Muons are identified in the K_L and muon system. However, its efficiency is very poor for low momentum muons that are out of acceptance of the dedicated sub-detector. Other sub-detectors designed for particle identification, the time of propagation detector and the aerogel ring-imaging Cherenkov detector, are not able to provide efficient μ/π separation in this momentum range because at low momenta multiple scattering in the material of the detector as well as the material in front of it blurs the pattern considerably.

Our main goal is to improve the identification of low momentum leptons using the information of energy deposition in the electromagnetic calorimeter in a form of images. As a classifier we are using a Convolutional Neural Network (CNN), a powerful machine learning technique designed for working with two-dimensional images. Using CNN on the images allows us to access the information on the shape of the energy deposition without depending on cluster reconstruction or track-cluster matching.

In what follows, we will describe the electromagnetic calorimeter of Belle II, discuss the analysis of simulated pion, muon and electron patterns in the electromagnetic calorimeter, and present the results.

2. Electromagnetic calorimeter of Belle II

The Belle II detector is a large-solid-angle magnetic spectrometer designed to reconstruct the products of collisions produced by the SuperKEKB collider. The detector consists of several sub-detectors arranged around the interaction point in cylindrical geometry: the innermost Vertex Detector (VXD) used for reconstructing decay vertices, a combination of the Pixel Detector (PXD) and Silicon Vertex Detector (SVD); the Central Drift Chamber (CDC) is the main tracking system; the Time of Propagation (TOP) detector in the barrel region and

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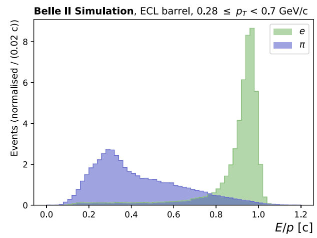
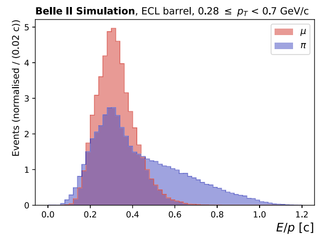


(a) e and π



(b) μ and π

Fig. 1. Distribution of E/p for simulated single particle candidates for $0.28 \leq p_T < 0.7$ GeV/c in the ECL barrel region.

the Aerogel Ring-Imaging Cherenkov detector (ARICH) in the forward endcap region are used for hadron identification; the Electromagnetic Calorimeter (ECL) is used to measure the energy of photons and electrons and the outermost K-Long and Muon (KLM) detector detects muons and neutral K_L^0 mesons [1].

The sub-detector relevant for this work is the ECL, more specifically its central barrel region which consists of 6624 CsI(Tl) scintillation crystals, covering the polar angle region $32.2° < \theta < 128.7°$ with respect to the beam axis. A solenoid surrounding the calorimeter generates a uniform 1.5 T magnetic field filling its inner volume [2]. We are mainly interested in the transverse momentum range $0.28 < p_T < 0.7$ GeV/c, where the minimal p_T threshold ensures the tracks are within the ECL barrel region acceptance. Currently, two methods for the particle identification in the ECL are available. The first method relies exclusively on the ratio of the energy deposited by a charged particle in the ECL and the reconstructed momentum of topologically matched charged track, E/p. While for electrons this variable enables powerful discrimination, as electrons completely deposit their energy in the ECL (Fig. 1(a)), the μ/π separation is strongly limited, especially for low-momentum particles with a broader E/p distribution (Fig. 1(b)). The second method uses Boosted Decision Trees (BDT) with several expert-engineered observables characterizing the shower shape in the ECL [4].

3. Analysis of the patterns in the electromagnetic calorimeter

Our proposed method to improve the identification of low-momentum leptons is to exploit the specific patterns in the spatial distribution of energy deposition in the ECL crystals using a Convolutional Neural Network (CNN).[1] The images are consistent with the 11×11 neighbouring crystals around the entry point of the extrapolated track into the ECL, where each pixel corresponds to an individual ECL crystal and pixel intensity to the energy deposited by charged particle in the crystal. While electrons generate electromagnetic showers depositing the majority of their energy in the ECL, the dominant interaction in CsI(Tl) for muons and pions in the aforementioned transverse-momentum range is ionization. Besides, pions can strongly interact with nuclei producing less localized images compared to muons [5]. Examples of the obtained images are shown in Fig. 2. Patterns of energy depositions also depend on transverse momentum, where at lower p_T the tracks in the magnetic field are strongly bent and the path through ECL is longer, what can be seen as the elongation in the horizontal direction of the averaged images in Fig. 2.

For each binary classification we generated 1.5×10^6 events using the Belle II Analysis Software Framework [6], where the data set consists of the same number of signal (e or μ) and background (π) events with uniformly distributed transverse momenta, polar angle and azimuthal angle. The two data sets were split on the train–validation–test set as

[1] CNN is built using TensorFlow software available from tensorflow.org.

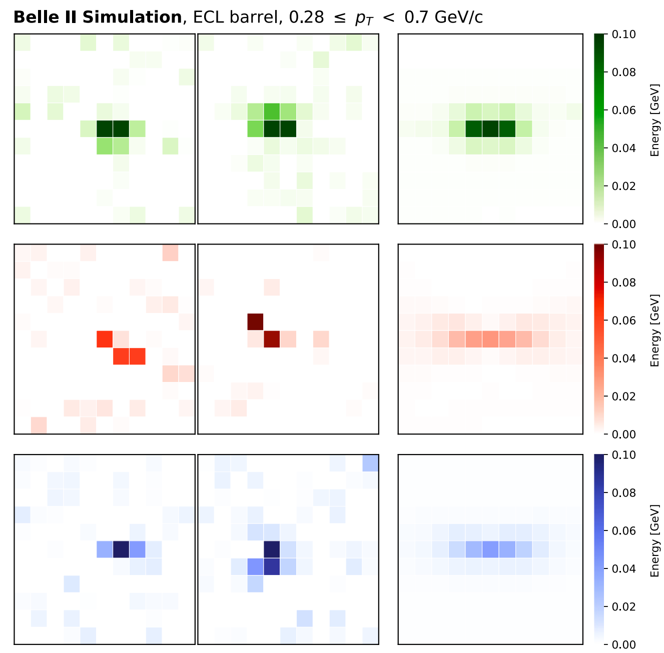
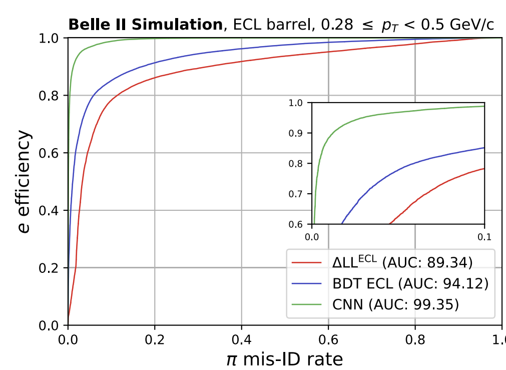
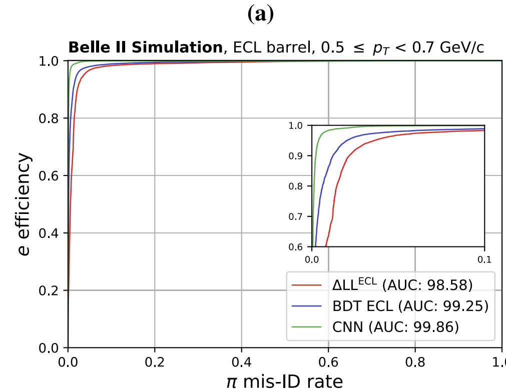


Fig. 2. Typical patterns of simulated energy depositions (first two columns) and the average over 80000 images (third column) for e (top), μ (middle) and π (bottom).



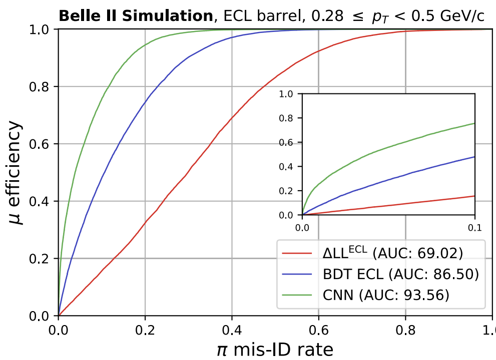
(a)



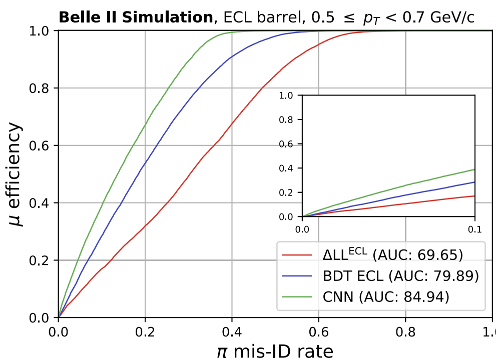
(b)

Fig. 3. The performance of three different classifiers for e/π based on only ECL information: $\Delta\mathrm{LL}^{\mathrm{ECL}}$, BDT ECL, and $\Delta\mathrm{LL}^{\mathrm{CNN}}$ in two different momentum regions (a) $0.28 \leq p_T < 0.5$ GeV/c and (b) $0.5 \leq p_T < 0.7$ GeV/c.

$70 - 10 - 20\%$ and we use the same CNN architecture for e/π and μ/π case. As an input to the convolutional layers we use 11×11 images. Before fully connected layers we add the information about p_T and



(a)



(b)

Fig. 4. The performance of three different classifiers for μ/π based on only ECL information: $\Delta\mathrm{LL}^{\mathrm{ECL}}$, BDT ECL, and $\Delta\mathrm{LL}^{\mathrm{CNN}}$ in two different momentum regions (a) $0.28 \leq p_T < 0.5$ GeV/c and (b) $0.5 \leq p_T < 0.7$ GeV/c.

θ_{ID}, where the later represents an integer number corresponding to the location of the ECL crystal and is in the network implemented as an embedding. To perform a binary classification, we have 1 neuron in the output layer with a sigmoid activation function that outputs the signal probability that the image was produced by a lepton.

4. Performance

To validate the performance of a binary classifier we use a Receiver Operating Characteristic (ROC) curve by plotting true positive rate (μ or e efficiency) against the false positive rate (π mis-ID rate). As the reference for the existing ECL information, we use the log-likelihood difference, a powerful discriminator between the competing hypotheses, defined as $\Delta\mathrm{LL}^{\mathrm{ECL}} = \log \mathrm{L}^{\mathrm{ECL}}_{e,\mu} - \log \mathrm{L}^{\mathrm{ECL}}_{\pi}$ based only on E/p [3] and BDT ECL using the shower-shape information from the ECL, thoroughly described in [4]. The ROC curves obtained by these three methods are shown in Fig. 3 for e/π and in Fig. 4 for μ/π classification.

Looking at the shapes of ROC curves and the Area Under the Curve (AUC) values, it is evident that the CNN outperforms the existing classifiers, $\Delta\mathrm{LL}^{\mathrm{ECL}}$ and BDT ECL for both e/π and μ/π. The performance of the CNN drops with increasing momentum as the path in the ECL gets shorter and the specific patterns in the images become less evident.

5. Summary and outlook

We can conclude there is more information in the ECL than is currently used for particle identification. We saw that the separation between low-momentum light leptons and pions can be improved using a CNN on the ECL images. To validate the CNN method and to test if the performance gain seen on the simulated sample also translates on real data we could use highly pure samples of electrons, muons and pions from $e^+e^- \rightarrow e^+e^-(\gamma)$, $e^+e^- \rightarrow \mu^+\mu^-\gamma$ and $K^0_S \rightarrow \pi^+\pi^-$, respectively. The newly proposed method looks very promising and worthwhile to be further developed. A comparison of the method presented in this article to a novel BDT-based analysis is a subject of a forthcoming publication [7].

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