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Machine Learning Particle Classifier for Water Cherenkov Detectors Hyper-Kamiokande neutrino experiment

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Figure 1: WCD scheme

- Subatomic elementary particles
- Mysterious but yet abundant
- Very elusive
- Key in the understanding of our Universe
- Indirect detection (Cherenkov effect)
- Binary classification: e^- vs. γ background

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Figure 2: Schematic of the IWCD detector [1]

- Based in Japan
- Expected to be completed in 2027
- Software including ML algorithms
- IWCD at 0.7-2 km from source
- h=6m, r=4m
- 536 mPMT modules (19 PMTs each)
- PMT records charge and time
- Use time as a performance booster



Figure 3: mPMT module design for HK [2]

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Dataset					

- Simulated data (using WCSim)
- Around 3M events
- Balanced dataset
- Uniform distributions



Figure 4: Coordinate system



Figure 5: Event distributions (metadata)

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From Data	to Images				



Figure 6: PMTs in 3D tank



Figure 7: Original image size



Figure 8: mPMTs in unwrapped tank



Figure 9: mPMT charge sum for an event

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Time infor	mation				



Figure 10: Event distributions

$$ilde{q} = rac{q}{1+rac{|t-\mu_t|}{\sigma_t}}$$
 (1)

Approaches:

- As channel (charge-like)
- Embeded in scaling factor (1)
- Order pixel features chronologically

Add-ons:

- Scaling: hit standardization
- mPMT aggragated representation (mean and standard deviation)



Figure 11: Hybrid representation

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Uncertainty measures:

- Variance
- Margin of confidence
- Entropy
- Mutual information

Bhattacharyya distance to discriminate correct and incorrect prediction populations:

$$D_B(\mathbf{p},\mathbf{q}) = -\ln\left(\sum_i \sqrt{p_i q_i}\right)$$



Figure 12: MCD concept [3]

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Time infor	mation						
Considere	d experiments:		Configurat	ion:			
 Charge and/or Time 			• ResNet 18				
Hit standardization or None			• 20 epochs (\sim 9 hours)				
• mPMT agg. or 19 features			• Batch size: 512 • Adam with $k = 1 \times 10^{-4}$				

- Time as scaling factor
- Chronological pixel ordering

- Adam with lr = 1
- Fixed seed
- I transformation

Model	Loss	Accuracy	F_1 score	AUC	$\sigma_{\sf AUC}$
Q+Ts	0.6037	0.6713	0.6613	0.7332	0.0009
Qs+Ts	0.6042	0.6705	0.6601	0.7328	0.0014
Q+T	0.6106	0.6642	0.6481	0.7254	0.0013
Original	0.6272	0.6426	0.6201	0.7004	0.0010

Table 1: Average value of the loss function and performance metrics along with the standard deviation in the AUC.

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Dropout					



Figure 13: AUC values for different drop-neuron/channel dropout rates in training



Figure 14: AUC values for different drop-neuron/channel dropout rates in validation

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Figure 15: Bhattacharyya distance for different models and drop- neuron/channel dropout rates using the margin of confidence as uncertainty measure

$$egin{aligned} \mathcal{M} &= rac{1}{T}\sum_{t=1}^{T}| \mathcal{p}_{1}^{t} - \mathcal{p}_{0}^{t}| \ \mathcal{D}_{B}(\mathbf{p},\mathbf{q}) &= -\ln\left(\sum_{i}\sqrt{\mathcal{p}_{i}\mathcal{q}_{i}}
ight) \end{aligned}$$



Figure 16: Histogram of correct and incorrect predictions for the margin of confidence and its discriminating power using the Bhattacharyya distance

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	Model	Loss	Accuracy	F ₁ score	AUC	-	
	Proposed Original	0.5856 0.6271	0.6864 0.6427	0.6795 0.6203	0.7550 0.7007		

Table 2: Loss function evaluated in the test set along with some performance metrics for the original configuration and the proposed model



Figure 17: Row normalized confusion matrix for both original and proposed models

	Total	Electron	Gamma
Confidence (%) \mid	38	39,1	37

Table 3: Mean confidence values of test set predictions

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Figure 18: Proposed and original models compared in terms of performance for different features and confidence for both classes

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Conclusions					

- Time as a channel
- Hit standardization
- Hybrid representation: time mPMT aggregated
- Relative accuracy improvement of 7%
- Relative electron signal efficiency improvement of 16%
- Outputting margin of confidence in every prediction using MCD
- Enhanced and more stable behaviour towards different energy ranges, cone vertex positions and particle directions

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Thank you!

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Figure 19: Map of the HK neutrino experiment with the main detector, the IWCD, the near detector and the source of neutrinos (J-Parc accelerator).





Figure 20: Sum of charge per mPMT for an electron event before and after padding



Figure 21: Sum of charge and average time detection per mPMT for a gamma event