Smart Rifle Training: Shot Detection using Motion Data and Embedded Machine Learning

DIE UNTERNEHMERISCHE HOCHSCHULE

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INTRODUCTION

In long-range shooting sports, athletes compete by hitting targets at distances of up to a thousand yards. To achieve competitive levels of precision and accuracy, athletes require frequent training.

Dry-firing is an alternative method for practicing off-range **[1]**. Identifying areas for improving an athlete's form can be supported by systems equipped with sensors such as the MantisX shooting performance system **[2]**. Reliable shot detection is essential for capturing the time window relevant for analysis. Motion sensors can detect live-fire events, if the recoil is powerful enough. During dry-fire training, releasing the firing pin results in a comparatively low-amplitude signal. Therefore, higher sensitivity is needed for detection, making such systems prone to register false positives.

This work aims to determine if a machine learning model deployed on a microcontroller as a part of a TinyML application **[3]** can differentiate between live-fire-, dry-fire, and non-shot events such as reloading or unintended collisions.

METHODS

Data was collected using a 6-axis motion sensor connected to a microcontroller. Firmware for the controller and a mobile application were developed to enable the wireless transfer of recorded motion data to a smartphone.

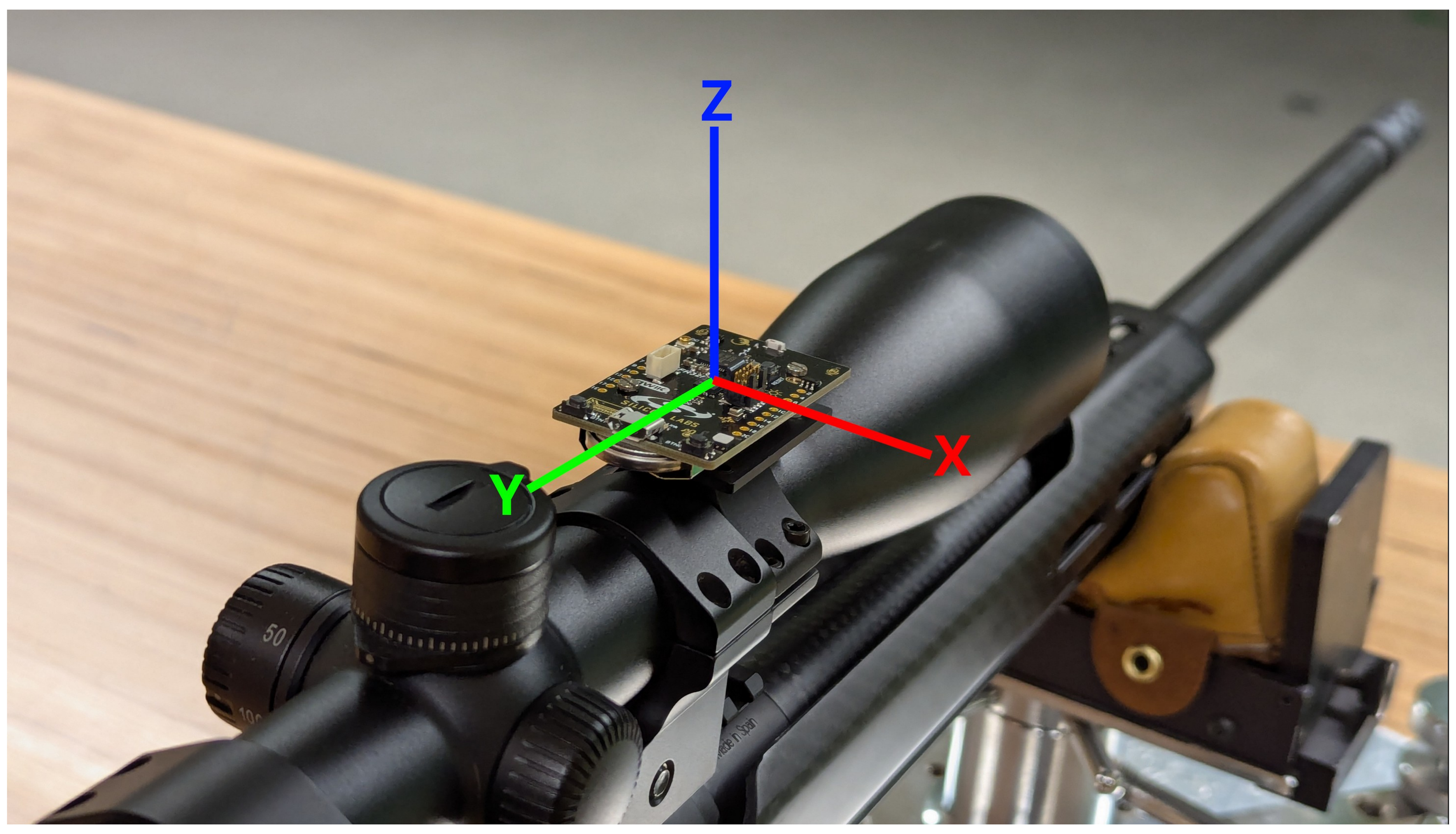

Fig. 1: Motion sensor system mounted on rifle scope

Each recorded sample contains the values for acceleration and angular velocity in a time window of 500 ms before and after a motion event occurred. 857 Samples consisting of "live-fire", "dry-fire" and "non-shot" events, were acquired using five different rifle setups with the help of five participants. To increase the size of the dataset, Data-augmenntation was used to generate new samples based on the recordings resulting in a dataset size of 18247 samples.

The dataset was balanced using downsampling, shuffled with a stratified shuffle and partitioned into training and validation sets using a 80 to 20 split. Using TensorFlow **[4]**, a 1D Convolutional Neural Network (CNN) based on the architecture shown in Fig. 2 was then trained for 10 epochs. The resulting model was quantized and deployed to the microcontroller.

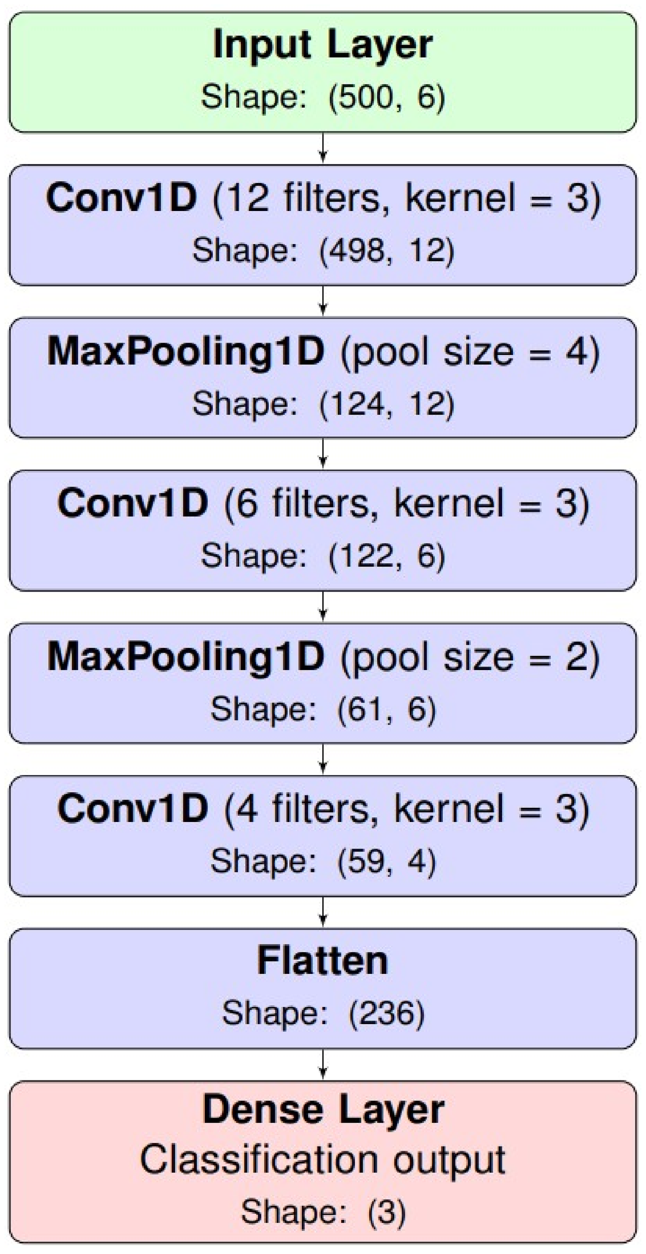

Fig. 2: CNN Model Architecture

RESULTS

Tab. 1 shows the classification results of the model on the validation dataset after the model was converted to the TFLite format and quantized to the INT8 format. The confusion matrix in Fig. 3 shows the number of correct and incorrect predictions for each class.

Tab. 1: Model training performance metrics

Class	Precision	Recall	F1-Score	Support
none	0.95	0.97	0.96	215
dry	0.97	0.95	0.96	215
live	1.00	1.00	1.00	215
Accuracy			0.98	645
Macro Avg	0.98	0.98	0.98	645
Weighted Avg	0.98	0.98	0.98	645

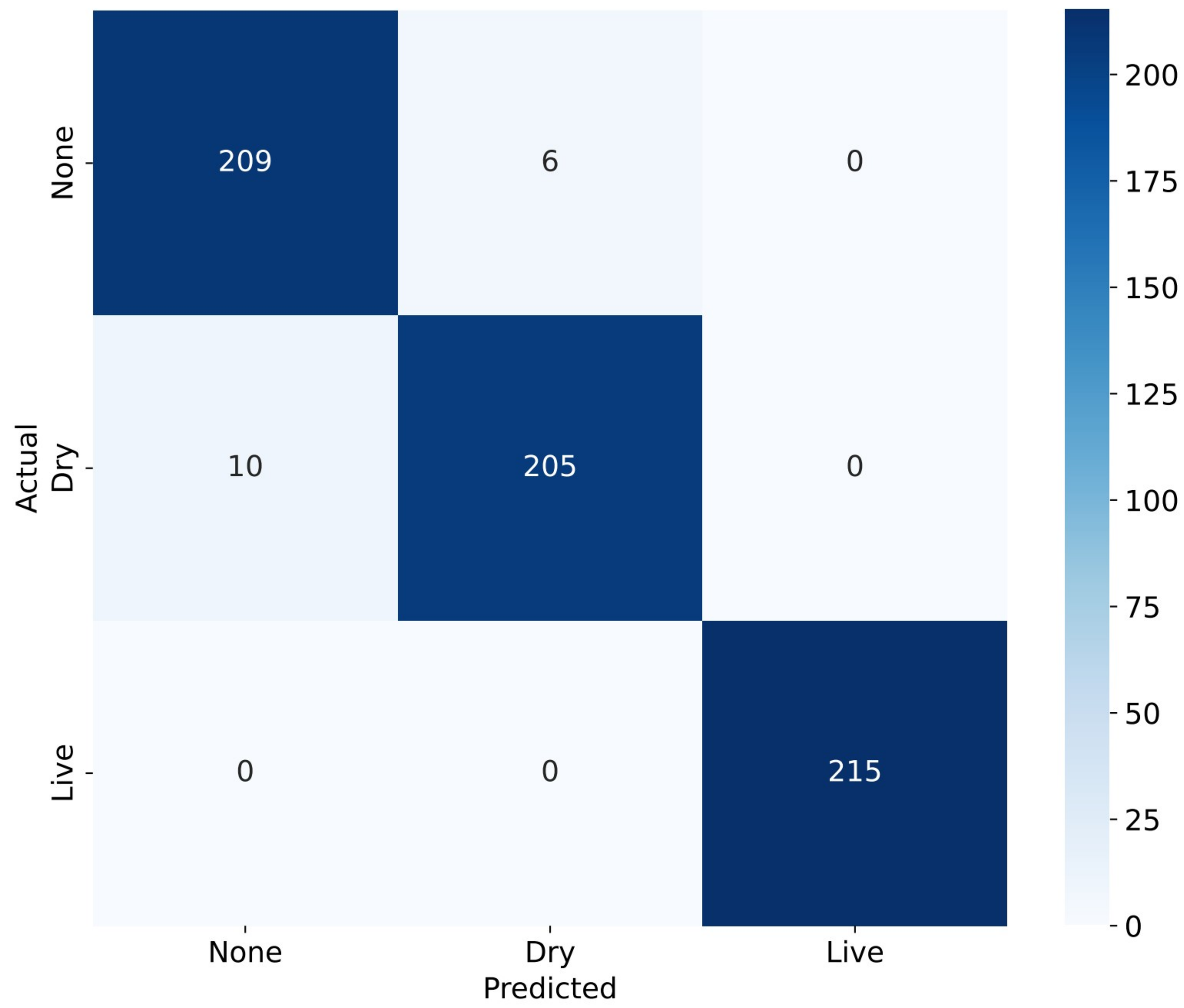

Fig. 3: Confusion Matrix of shot detection model

The model was deployed to the microcontroller and compared against the MantisX **[2]** shooting performance system. Both shot detection systems were mounted on one of two rifle systems. A series of 20 live shots and 20 dry shots was performed with each setup. Tab. 2 lists the results of the comparison.

Tab. 2: Comparing ML-based shot detection against MantisX [2] system

		Setup 1		Setup 2	
Event	**Metric**	**TinyML**	**MantisX**	**TinyML**	**MantisX**
Live-Fire	True Positives	20/20	20/20	20/20	20/20
	False Negatives	0/20	0/20	0/20	0/20
	False Positives	0	0	0	0
Dry-Fire	True Positives	18/20	20/20	19/20	20/20
	False Negatives	2/20	0/20	1/20	0/20
	False Positives	0	61	0	13
Misclassifications		0	-	0	-

CONCLUSION

Compared to existing systems, the ML-based method for shot-event detection enhances functionality and reliability. The application accurately registers shot events and introduces dry-fire detection for bolt action rifles which provides the foundation for further development of ML applications for shooting sports athletes.

References: **[1]** R. M. Cleckner, Long Range Shooting Handbook, 1st ed. North Shadow Press, Feb. 2016.
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[3] P. Warden and D. Situnayake, TinyML: Machine Learning with TensorFlow Lite on Arduino and Ultra-Low-Power Microcontrollers, 1st ed. O'Reilly Media, Inc., Dec. 2019,
[4] Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Rafal Jozefowicz, Yangqing Jia, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dan Mané, Mike Schuster, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. TensorFlow: Large-scale machine learning on heterogeneous systems, 2015. Software available from tensorflow.org