# Event-based vision for improved classification accuracy in label-free flow cytometry

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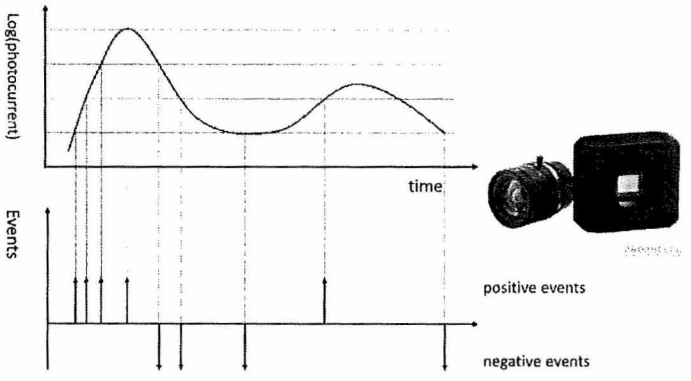
## *Abstract*

*Event-based cameras are cutting-edge, bio-inspired vision sensors that differ from conventional frame-based cameras in their operating principles. In the field of machine learning, the switch from CMOS cameras to event-based cameras has improved accuracy in settings with critical illumination and rapid dynamics. In this work, we examine the combination of event cameras with extreme learning machines in the context of imaging flow cytometry. The experimental setup, with the exception of the image sensor, is similar to a set-up we utilized in a previous work in which we demonstrated that a simple linear classifier can achieve an error rate of about 10% on background-subtracted cell frames. Here, we demonstrate that by utilizing an event camera's capabilities, the error rate of this basic imaging flow cytometer could be reduced to the order of* $10^{-3}$. *Additionally, advantages like increased sensitivity and effective memory utilization are obtained. Finally, we make further suggestions for potential upgrades to the experimental setup that records events from moving microparticles which will enable more precise and reliable cell sorting.*

## Introduction




The biomedical sector employs a tool called flow cytometry to analyze a large number of cells or particles [1]. The technique has been used in a variety of applications, including the progression of cancer therapy and cancer detection, as well as the categorization of microparticles and microalgae [2,3].

In this work, we use PROPHESEE's event-based camera (also called a dynamic vision sensors DVS) in imaging flow cytometry to overcome two main drawbacks faced by systems which rely on traditional CMOS (or frame-based) sensors. The two drawbacks of continuously capturing consecutive frames are memory usage and the difficulty of filtering the background noise. Since the machine learning training can be very sensitive to noise, not filtering noise properly could result in lower achievable classification accuracies. Since event-based cameras only capture the changes in the scene (Figure 1),

the background noise is automatically removed and the memory usage is much more efficient.

## Methods

A laser source generating light with a 632.8 nm wavelength makes up the configuration created for this work as seen in figure 2. The light is directed onto a PMMA microfluidic channel after passing via a lens and a 25 m pinhole. A manual syringe pump attached to the top port of the channel is used to pump flowing microparticles . One syringe was used for particle A, another for particle B, and a third one was used to wash out the system with water. The movement of the particles changes the diffraction pattern which is captured by a Prophesee event camera. We used two different classes of spherical microparticles (class A of diameter 16 μm and class B with a diameter of 20 μm).

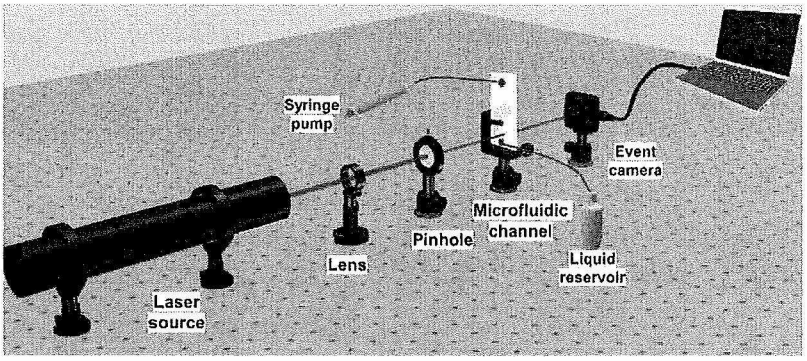



*Fig. 2: The experimental setup built to generate the training and test datasets. Light coming from a 1550 nm He-Ne laser passes through a lens then a 25 μm pinhole. Behind the pinhole is a vertically-mounted PMMA microfluidic channel inside which microparticles are flowing downwards. The diffraction pattern caused by a flowing particle is captured by the event-based camera which is connected to a laptop with a dedicated software for recording the events fired at different pixels.*

## Results

The events fired by the camera upon the passage of different particles inside the microfluidic channel were recorded by a laptop. We then build a machine learning pipeline which starts by first framing all the different events belonging to a certain sample as shown in figure 3. We compared such samples with a simulation model that was done in ASAP[1] using gaussian beam propagation method. The generated frames then went through different preprocessing steps (downsampling, flattening, standardization, feature

[1] ASAP is an optical simulation software for predicting real-world performance

selection), then a simple regularized logistic regression (a classification algorithm) was applied on the resulted feature matrix.

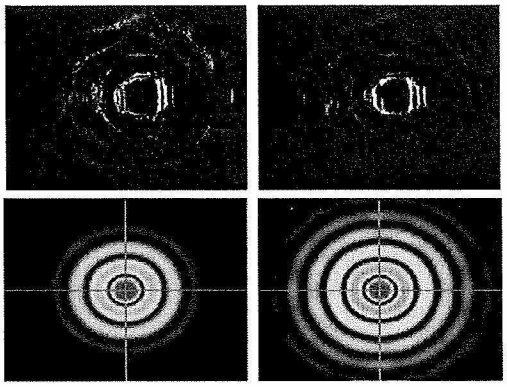


*Fig. 3: Experimental (top) and simulated (down) data of the diffraction pattern caused by the flowing microparticles. Particles with two different diameters were used, 16 μm (left) and 20 μm (right). The model was simulated using ASAP's waveoptics simulator. Notice the first disc of the airy pattern appears in the simulation model but not in the experimental frames. This is because the events in the center are not fired due to the fixed illumination.*

In machine learning, it is crucial to split the data into three different categories for training, validating and testing our model. At first, we had only one single measurement session from which we collected those three types of samples. However, we found that models trained and validated this way give misleading high accuracy when tested on the same measurement session's data. However, when we test such models on data from new experiments, we found that the accuracy drops significantly. Therefore, we decided to train our classifier in an intertwined way making it see data from different experiments while testing was done on data from unseen experiments during training. Figure 4 shows the error rates achieved by our trained classifier.

Finally, we compared the error rates of the current system with the one we had previously in [3] which used a CMOS camera. We found that we could decrease error rate by 2 orders of magnitude.

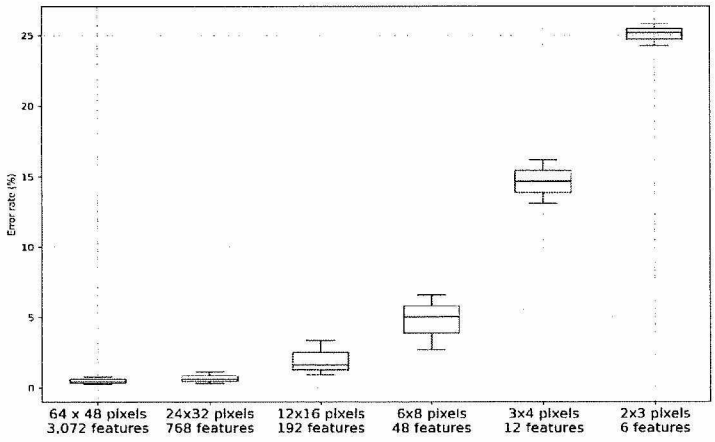



*Fig. 4: Test error rates for different classifier models trained using samples from different measurement sessions. The trained models were tested on unseen data from different sessions than those in either training or validation. On the x-axis are the resolutions of the frames sent to the linear classifier.*

## Conclusion

In this work we have demonstrated experimentally the different benefits novel event-based sensors bring to the field of flow cytometry. These included higher accuracy, lower background noise and more efficient memory utilization. We compared the new results with the results from previous work which used a frame-based camera. Future work encompass classifying biological cells and training spiking neural networks on the signal from the DVS sensor.

## ACKNOWLEDGMENTS

This work was performed in the context of the European H2020 Neoteric project (grant agreement 871330).

## References

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