



Seizure Detection Device

Using TinyML to detect epileptic seizures

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WHAT ARE SEIZURES?

Seizure types:

1. Generalized Seizures (Affect both brain hemispheres)

- Tonic-Clonic: Loss of consciousness, stiffening (tonic) followed by full-body jerking (clonic).
- Myoclonic: Sudden, brief muscle jerks.

2. Focal Seizures (Start in one brain region)

- Focal Motor: Repeated jerking in one limb or face.
- Focal Nonmotor: Can spread, leading to generalized seizures.

How can they be detected?

1. Electroencephalography (EEG):

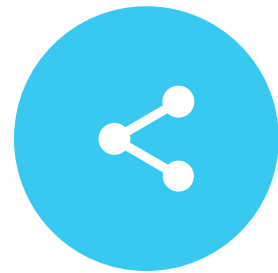
- Gold standard for seizure detection.
- Used in labs or via portable EEG devices.
- Effective in Epileptic Convulsion Recognition (ECR) but limited to short-term monitoring.

2. Wearable Technology:

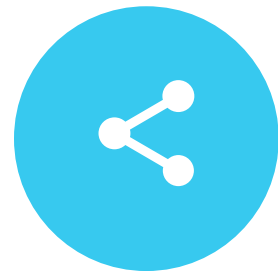
- Devices transmit data to smartphones and medical staff for enhanced diagnosis.

INTRODUCTION

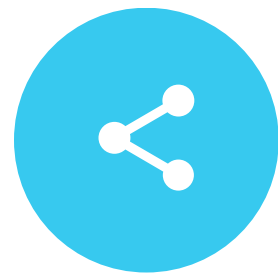
We need better seizure detection devices



Current seizure detection devices are large, expensive, and not energy-efficient.

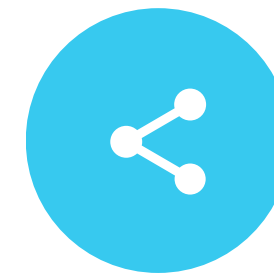


They often rely on cloud or phone-based processing, raising privacy concerns.

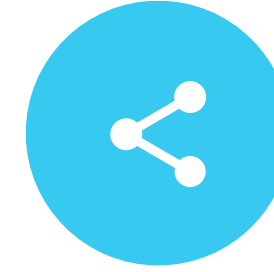


A wristband-based device can be lightweight, always on, and specifically designed for epilepsy patients

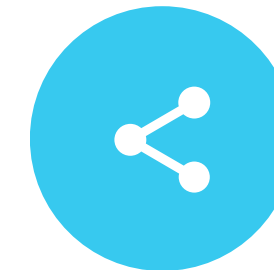
Key Considerations for an Effective Solution



Motion-based detection is non-invasive and cost-effective, but seizure movements are complex.



The device must balance accuracy, power efficiency, and real-time reliability.



A fully on-device system enhances privacy, reduces latency, and lowers costs compared to cloud-based alternatives.

LITERATURE REVIEW

Generalized Models for the Classification of Abnormal Movements in Daily Life and its Applicability to Epilepsy Convulsion Recognition [1]

Objective: identify epilepsy convulsions during daily activities using wearable devices

Method: comparing Support Vector Machines, k-Nearest Neighbors, and Decision Trees with Fuzzy systems

Results: indicated that Fuzzy Systems demonstrated superior generalization capabilities in recognizing clonic convulsions, effectively minimizing false alarms

[1] <https://pubmed.ncbi.nlm.nih.gov/27354194/>

WISDM Smartphone and Smartwatch Activity and Biometrics Dataset [2]

Objective: accelerometer and gyroscope data collected from 51 subjects performing 18 different daily activities for 3 minutes each, aiming to facilitate research in activity recognition and biometric identification.

Method: sliding window approach to segment the time-series sensor data into labeled examples, for ML applications

[2] <https://archive.ics.uci.edu/ml/machine-learning-databases/00507/WISDM-dataset-description.pdf>

DATASET CHARACTERISTICS

WISDM DATASET

- collected from 59 subjects
- Doing 18 activities (so 18 labels) - No epilepsy seizure data
- Used accelerometer and gyroscope data sampled at 20HZ
- Each activity lasted for ~ 3 minutes
- We only used data for 9 people and used it to enrich our model to generalize
- Relabeled all data to non-epileptic

EPILEPSY DATASET

- collected from 6 subjects
- Doing 4 activities (including epilepsy seizure simulation)
- Used accelerometer data sampled at 16Hz
- Each activity lasted for ~ 13 seconds
- We used all data to infer epileptic seizures
- Relabeled all data to Epileptic and non-epileptic

DATASET CHARACTERISTICS - DATA SNIPPET

WISDM DATASET

	accX	accY	accZ	Activity
0	9.397051	-1.127401	-1.061029	A
1	6.633513	0.187718	-0.440013	A
2	5.096351	2.329629	-0.079968	A
3	6.510423	1.363041	-0.363211	A
4	12.215082	-0.998780	-0.603777	A

EPILEPSY DATASET

	0x	0y	0z	1x	1y	1z	204z	205x	205y	205z	206x
0	0.60	-1.72	-0.47	0.60	-1.28	0.02	-0.51	-0.70	1.03	-0.57	EPILEPSY
1	-0.35	-0.99	0.05	-0.44	-2.30	0.05	0.55	-0.14	-0.34	0.83	EPILEPSY
2	-0.08	-1.02	-0.03	-0.01	-2.12	-0.48	-0.62	0.32	-0.67	-0.56	EPILEPSY
3	-0.43	0.78	-0.44	-0.44	0.78	-0.18	-0.46	-0.31	1.08	-0.59	EPILEPSY
4	-0.30	-2.40	-0.31	-0.81	0.80	-0.26	-0.03	-0.80	0.33	-0.02	EPILEPSY

BASELINE MODEL

%

ACCURACY

95.04%

Metrics for Classifier1

⬇️

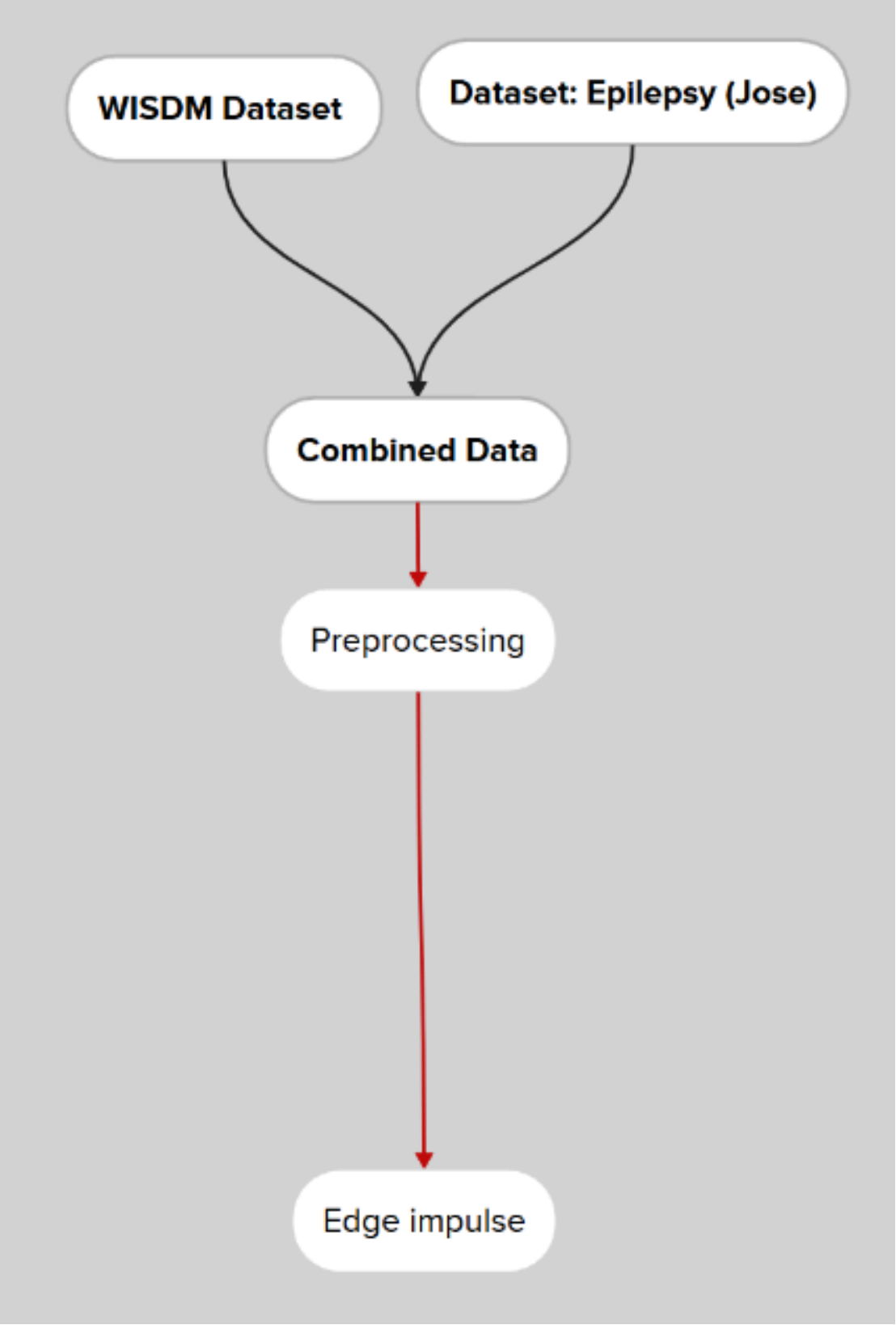
METRIC	VALUE
Area under ROC Curve ?	0.91
Weighted average Precision ?	0.96
Weighted average Recall ?	0.95
Weighted average F1 score ?	0.95

Confusion matrix

	EPILEPSY	NON-EPILEPTIC	UNCERTAIN
EPILEPSY	82.3%	16.1%	1.6%
NON-EPILEPTIC	0.1%	99.9%	0.1%
F1 SCORE	0.90	0.97	

- Only used the Epileptic data
- Default edge net impulse model used

MODEL DEFINITION AND EVALUATION



Training settings

Number of training cycles ?

30

Use learned optimizer ?

☐

Learning rate ?

0.0005

Training processor ?

CPU

Advanced training settings

Validation set size ?

20

%

Split train/validation set on metadata key ?

Batch size ?

32

Auto-weight classes ?

☒

Profile int8 model ?

☒

Neural network architecture

Input layer (1,504 features)

Dense layer (256 neurons)

Dropout (rate 0.2)

Dense layer (256 neurons)

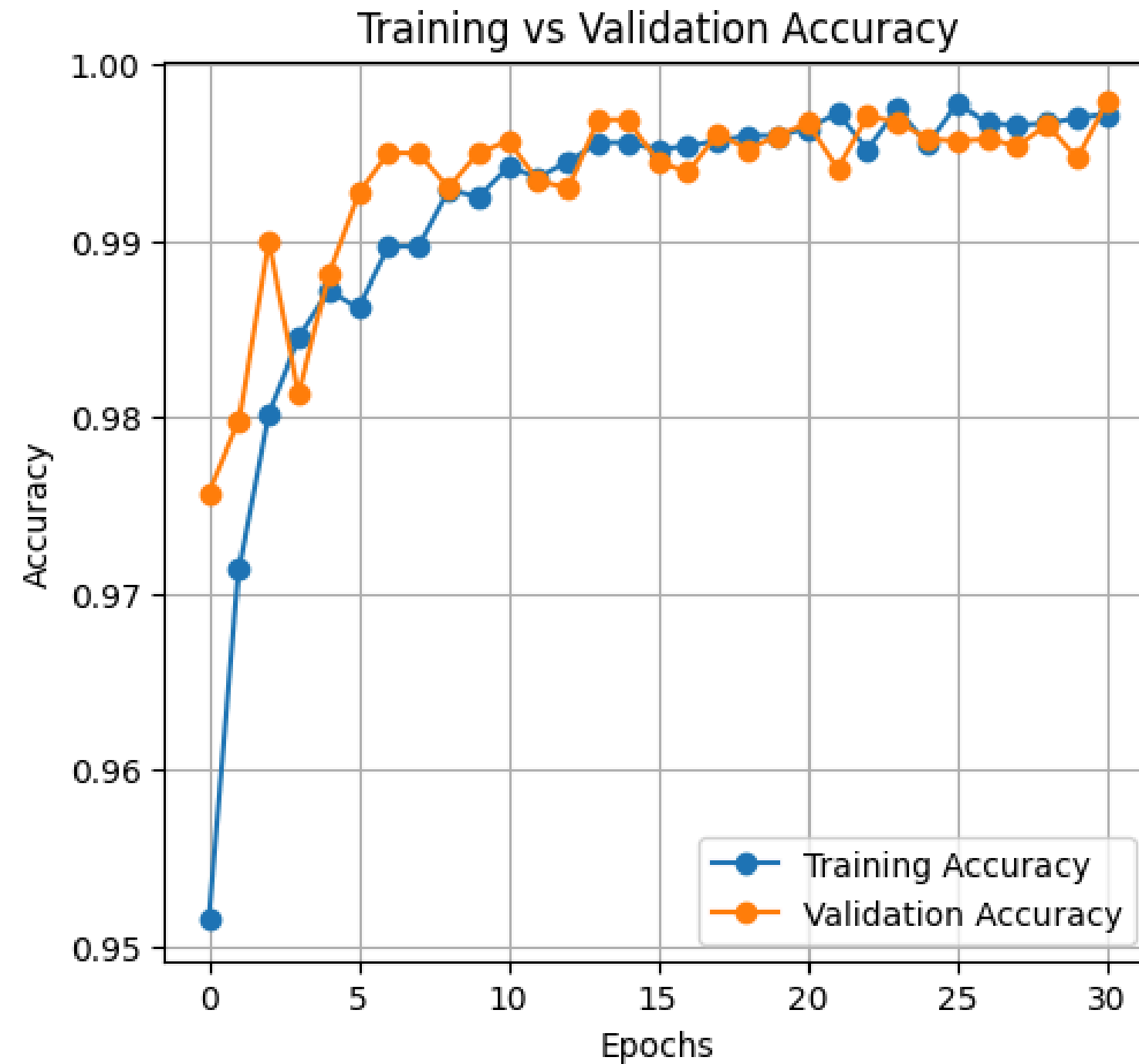
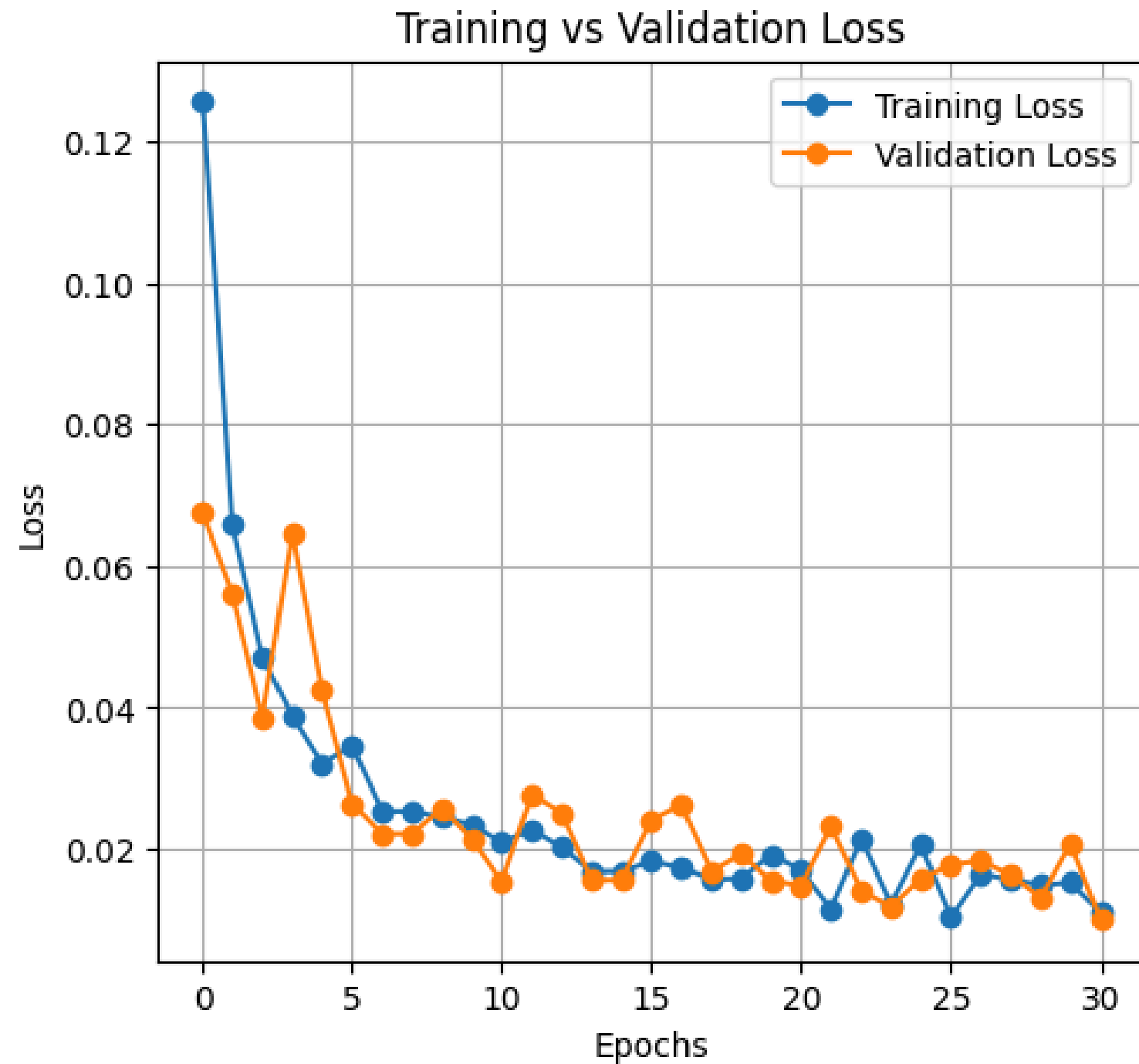
Dropout (rate 0.2)

Dense layer (256 neurons)

Dropout (rate 0.2)


Output layer (2 classes)

RESULTS



- combined data used for 9 people in WISDM dataset
- Optimized edge model with auto weights and more epochs

RESULTS







ACCURACY

99.76%

Metrics for Classifier1



METRIC	VALUE
Area under ROC Curve 	0.99
Weighted average Precision 	1.00
Weighted average Recall 	1.00
Weighted average F1 score 	1.00

Confusion matrix

	EPILEPSY	NON-EPILEPTIC	UNCERTAIN
EPILEPSY	99.1%	0.8%	0.1%
NON-EPILEPTIC	0.2%	99.8%	0.0%
F1 SCORE	0.96	1.00	

- combined data used for 9 people in WISDM dataset
- Optimized edge model with auto weights and more epochs
- Accuracy as well as the Epilepsy F1 score improved

CHALLENGES AND ERRORS

- Combining different datasets from different sources
 - different measurement devices
 - different measurement times
 - other unknowns?
- Simulating seizures ourselves
- Limited data for Seizures
- Deployment

DISCUSSION

- This is a proof of concept that it does work and be implemented in embedded systems.
- We cannot account for multiple forms of seizures yet
- We need more epileptic seizure data
- We have good test scores, but what do they mean?

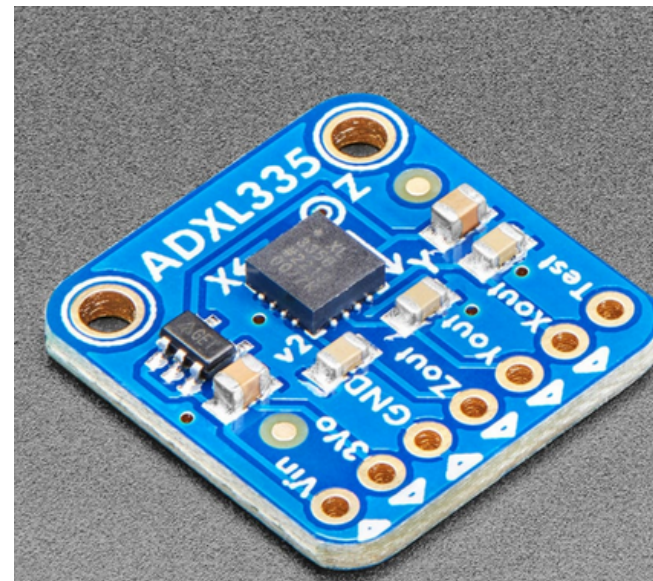
CONCLUSION

We implemented a Deep learning model in an embedded system to infer epileptic seizures with good test accuracies and F1 scores, proving that our model could accurately classify real time seizures with a wrist worn device and assist people with epilepsy.

FUTURE WORK

- Collect more data related to seizures to further test and train our model
 - <https://github.com/OpenSeizureDetector/OpenSeizureDatabase>
- Try out different model architectures
- Add more sensors
- Deploy our model on a prototype (Arduino, STM boards...) and design a wristband
- Start clinical testing with control and experimental group

<https://thepihut.com/products/adafruit-adxl335-5v-ready-triple-axis-accelerometer-3g-analog-out>



LIVE DEMO

Classify new data

Device ?

No devices connected

Sensor

Sample length (ms.)

13000

Frequency

Start sampling

Q&A



Thank you!

