

# Deep Neural Network based Cough Detection using Bed-mounted Accelerometer Measurements

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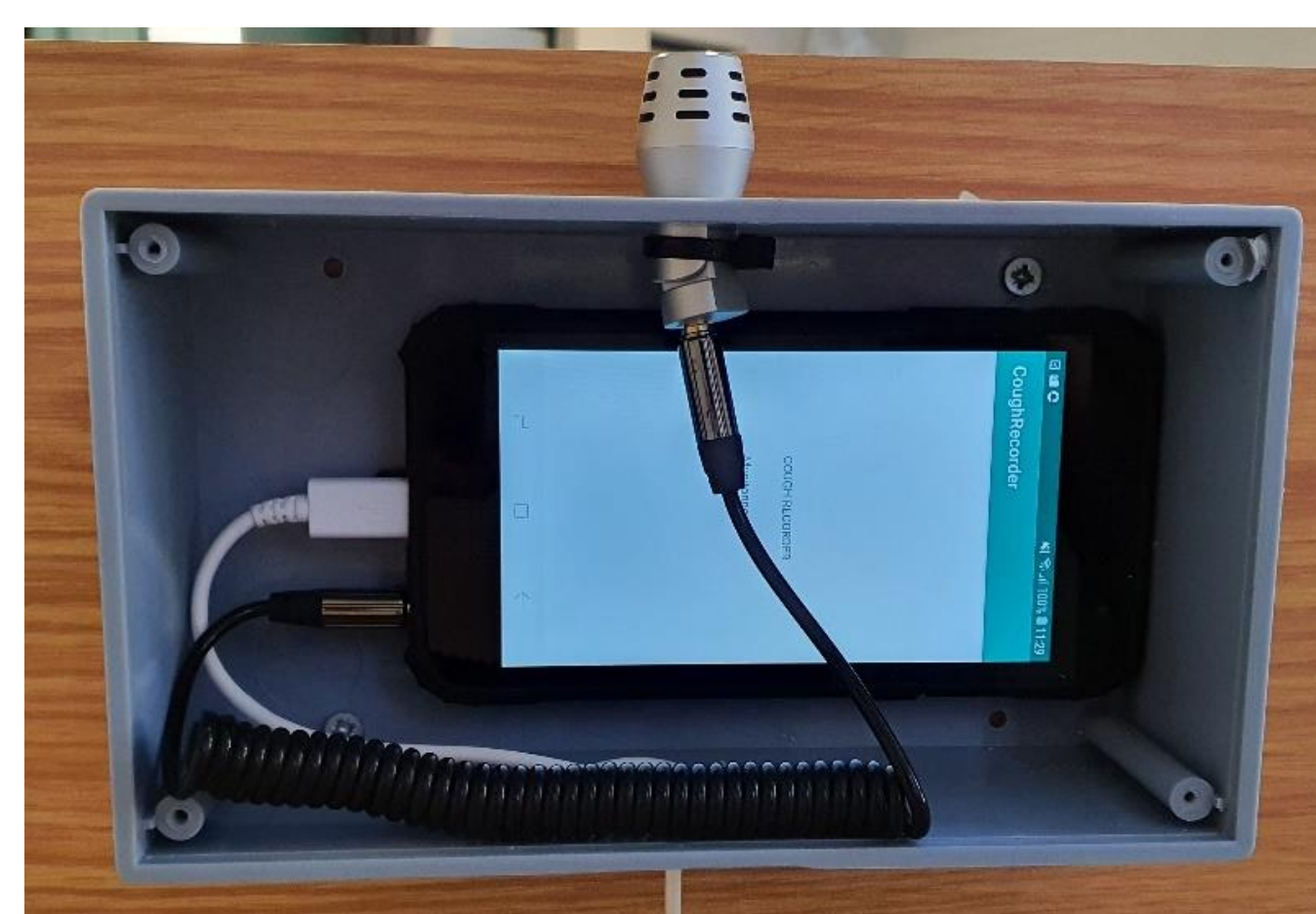
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## Introduction

We have performed deep neural network based cough detection using signals obtained from the integrated accelerometer of an inexpensive consumer smartphone attached to the patient's bed. Previously, body-attached accelerometers have been used to detect movements, including coughs, with high accuracy. However, this is inconvenient and intrusive. We propose this novel approach for long-term cough monitoring based only on signals obtained from bed-mounted accelerometers, eliminating the need to wear a measuring equipment.

## Data Collection

Data was collected at a small tuberculosis clinic near Cape Town, South Africa. A plastic enclosure housing an inexpensive smartphone running data gathering software is attached behind the headboard of each bed (Figure 1). Our ground truth dataset contained 6000 cough and 68000 non-cough events from 14 adult male patients.



A Samsung Galaxy J4 smartphone with an inbuilt accelerometer connected to an external BOYA BY-MM1 cardioid microphone by a 3.5 mm audio jack

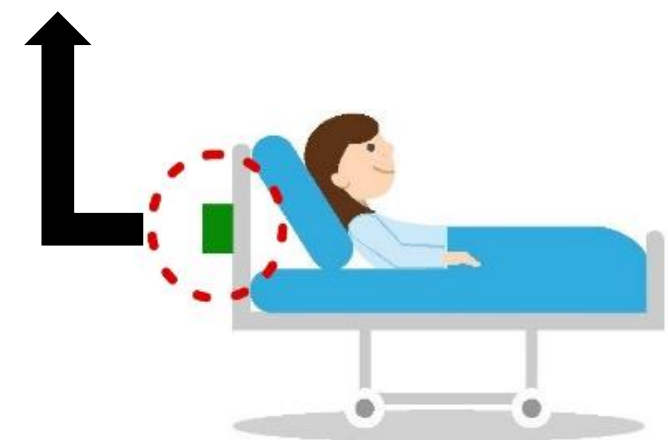


Figure 1: Data collection (recording) process

## Feature Extraction

Coughs are very distinctive in nature and mark their special patterns in both audio and accelerometer signals making them very unique.

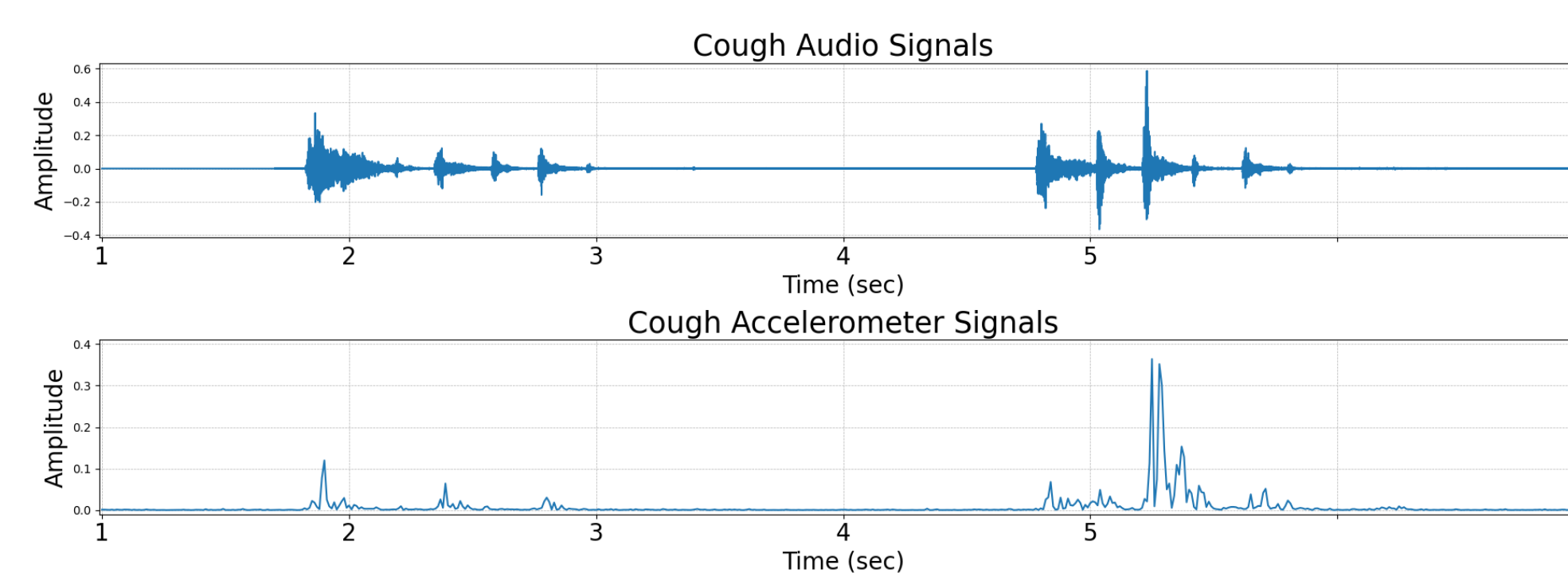


Figure 2: Cough audio and accelerometer signals

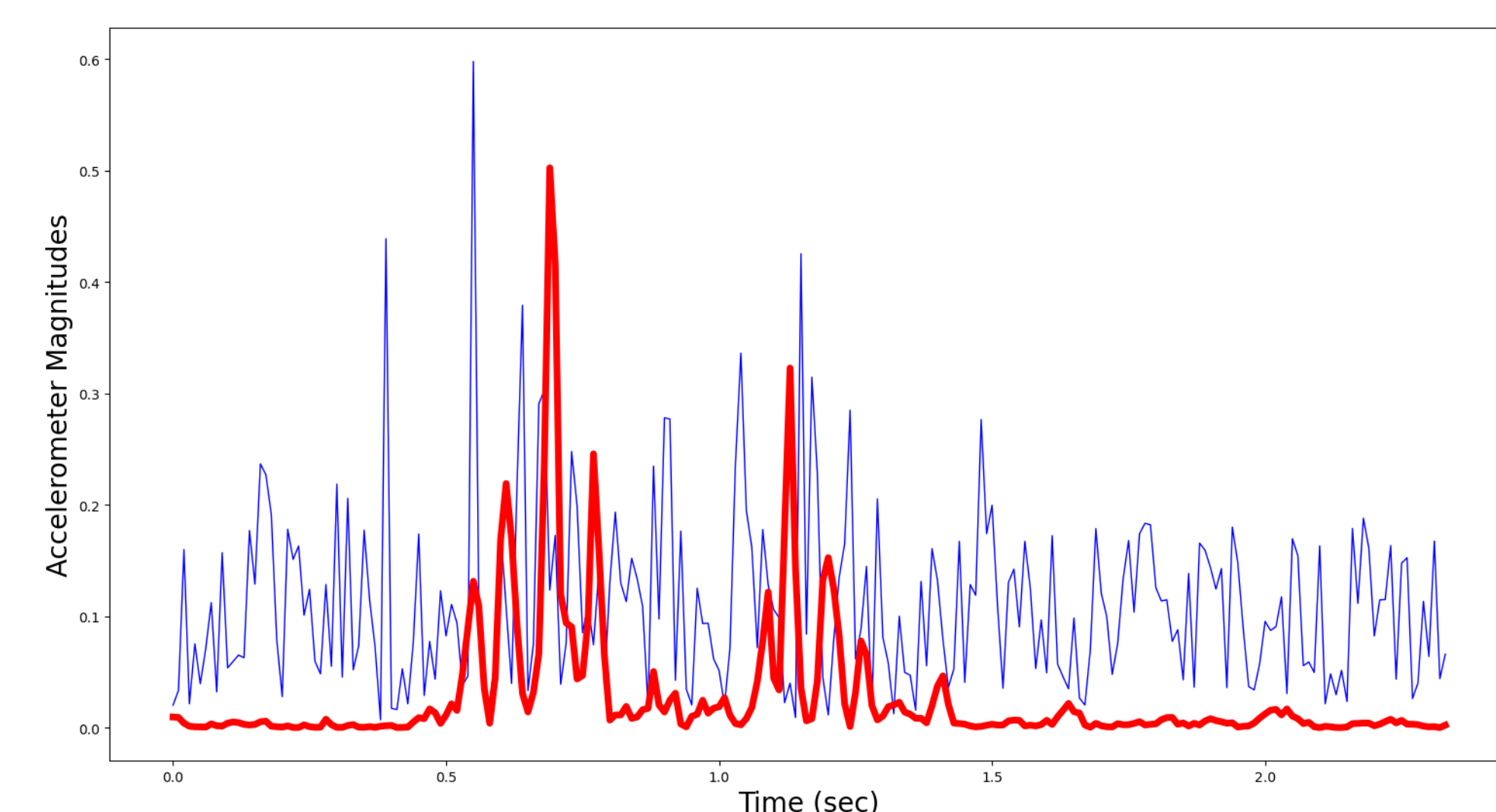


Figure 3: Cough vs non-cough accelerometer signal

Power spectra, root mean square amplitude, kurtosis, moving average and crest factor are extracted from the acceleration signals as features for cough detection with hyperparameters shown in Table 1. The input feature matrix has the dimension of  $(C, \frac{\Psi}{2} + 5)$  and power spectra have  $(\frac{\Psi}{2} + 1)$  coefficients.

Hyperparameter	Description	Range
	Size of frames in samples in which cough is segmented ( $\Psi$ )	$2^k$ where $k = 4, 5, 6$
	Number of segments in which frames were grouped ( $C$ )	5, 10

Table 1: Feature extraction hyperparameters

## Classifier Training

Deep neural networks such as the CNN, LSTM and Resnet50 were trained and evaluated by using leave-one-patient-out cross-validation. The following hyperparameters in Table 2 were optimised for the CNN and LSTM. Only the default 50 layer residual architecture (Resnet50) has been used.

Hyperparameters	Range
Batch Size ( $\xi_1$ )	$2^k$ where $k = 6, 7, 8$
No. of epochs ( $\xi_2$ )	10 to 200 in steps of 20
No. of Conv filters ( $\alpha_1$ )	$3 \times 2^k$ where $k = 3, 4, 5$
kernel size ( $\alpha_2$ )	2 and 3
Dropout rate ( $\alpha_3$ )	0.1 to 0.5 in steps of 0.2
Dense layer size ( $\alpha_4$ )	$2^k$ where $k = 4, 5$
LSTM units ( $\beta_1$ )	$2^k$ where $k = 6, 7, 8$
Learning rate ( $\beta_2$ )	$10^k$ where $k = -2, -3, -4$

Table 2: Classifier hyperparameters

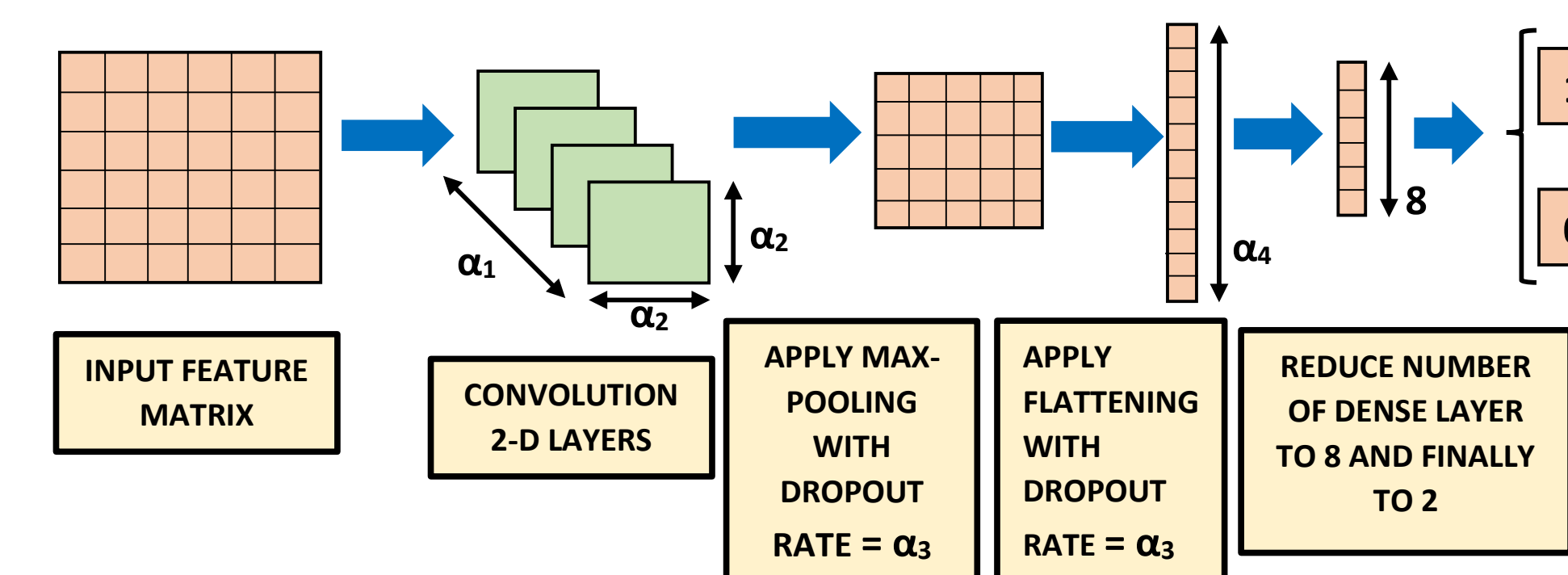


Figure 4: CNN architecture with hyperparameters

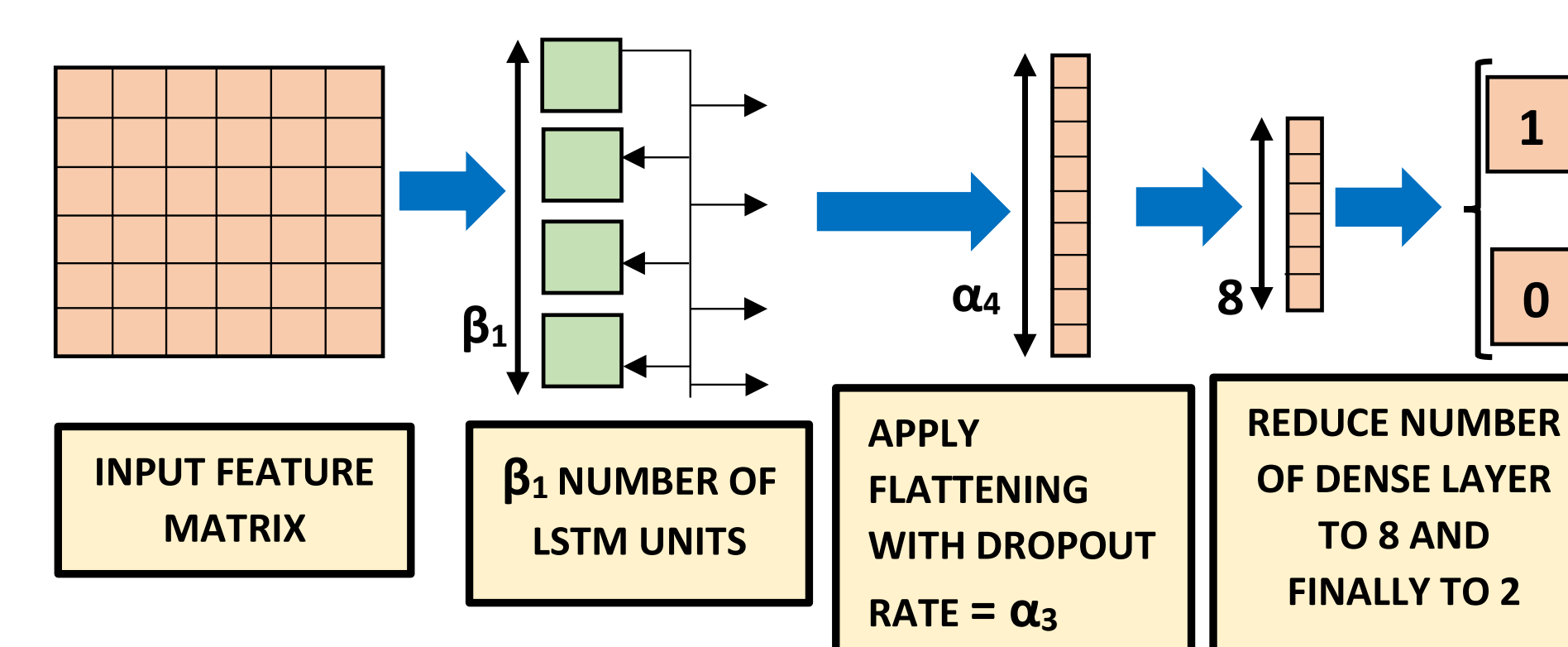


Figure 5: LSTM network with hyperparameters

The classifier performance is evaluated based on (are under the curve) AUC, averaged over 14 leave-one-patient-out cross-validation folds.

## Results

Best performance (AUC = 0.9888) is achieved by the Resnet50, outperforming the LSTM and CNN over a wide range of operating points (Figure 6).

Classifier	Frame (Ψ)	Seg (C)	Mean Spec	Mean Sens	Mean Accuracy	Mean AUC
CNN	64	10	91%	80%	86%	0.9499
LSTM	32	10	86%	93%	89%	0.9572
Resnet50	32	10	94%	99%	97%	0.9888

Table 3: Classifier results on cough detection

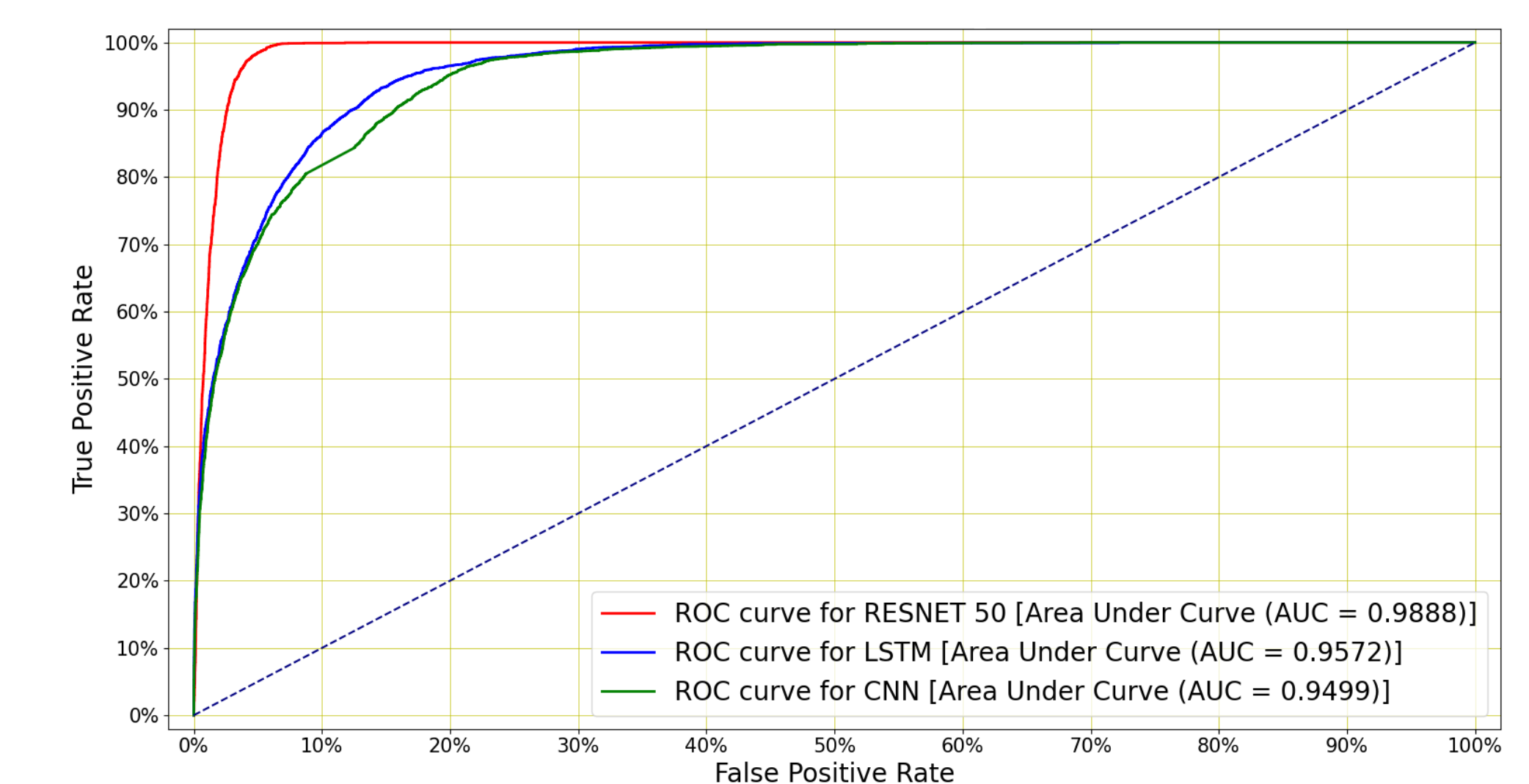


Figure 6: Mean ROC curves for cough detection

## Conclusion

All three deep neural network classifiers were able to detect cough and non-cough events in the accelerometer signals as captured by a consumer smartphone attached to a patient's bed. The highest AUC of 0.99 has been achieved by the Resnet50. This presents a less intrusive method of cough monitoring than body-mounted accelerometers. It can be of practical use in monitoring the long-term recovery process of patients, for example in the clinic where the data was collected. This form of cough monitoring also sidesteps privacy concerns encountered when using audio for cough detection.