Linear Prediction Residual for Efficient Diagnosis of Parkinson’s Disease from Gait

Parkinson's Disease

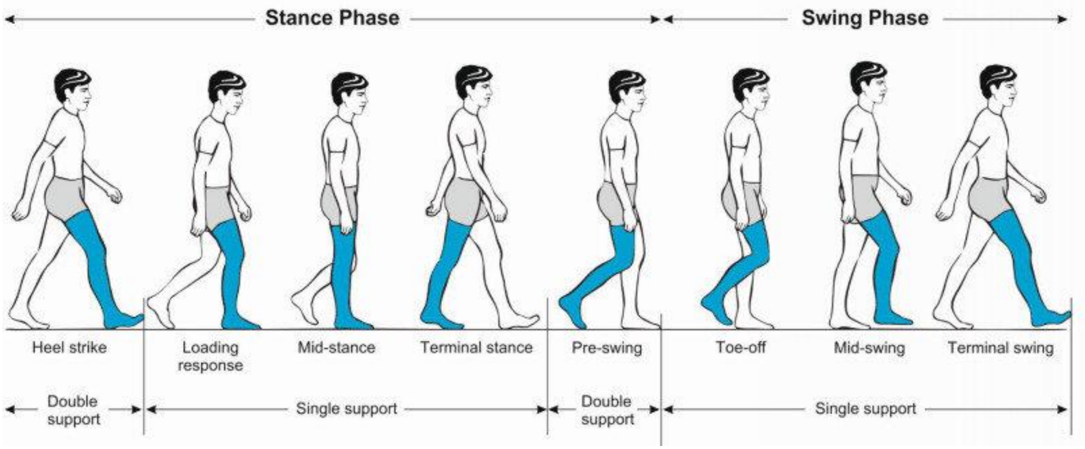
- Parkinson’s Disease (PD) is a neurological disorder that affects neurons responsible for motor control.
- Second most common neurological disorder after Alzheimer’s.
- Affects about 10 million people worldwide and is considered a chronic disease.
- PD diagnosis is a clinical exercise as there is no definite medical test for diagnosis.
- 10-30% of the patients initially diagnosed with PD are later diagnosed differently.
- Although there is no known cure, several therapies have shown promise to improve the quality of life of affected patients.

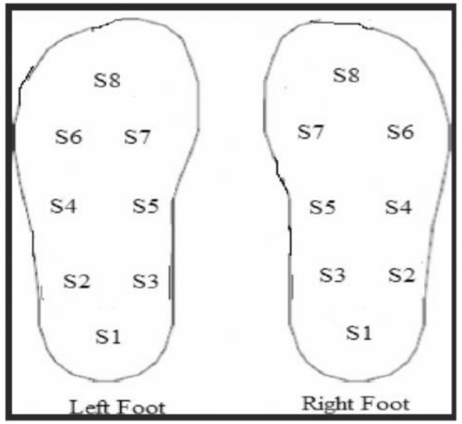
Related Work

- Attempts have been made to build models that diagnose PD from handwriting patterns, speech and gait patterns.
- Handwriting patterns and speech are not as general as gait.
- Speech and handwriting can have large variabilty between differnet cohorts.
- In this work we attempt to build efficient models for diagnosing PD from gait patterns.

Dataset

- 306 gait recordings from 166 subjects.
- 93 patients with PD subjects and 73 healthy control subjects
- Each recording is a two-minute-long measurement of Vertical Ground Reaction Forces (VGRF)
- VGRF measured at 8 points under each foot at a sampling rate of 100hz
- 18 time series in each recording.
    - 8+8 (16) series from each sensor.
    - 2 series representing total forces under each foot.





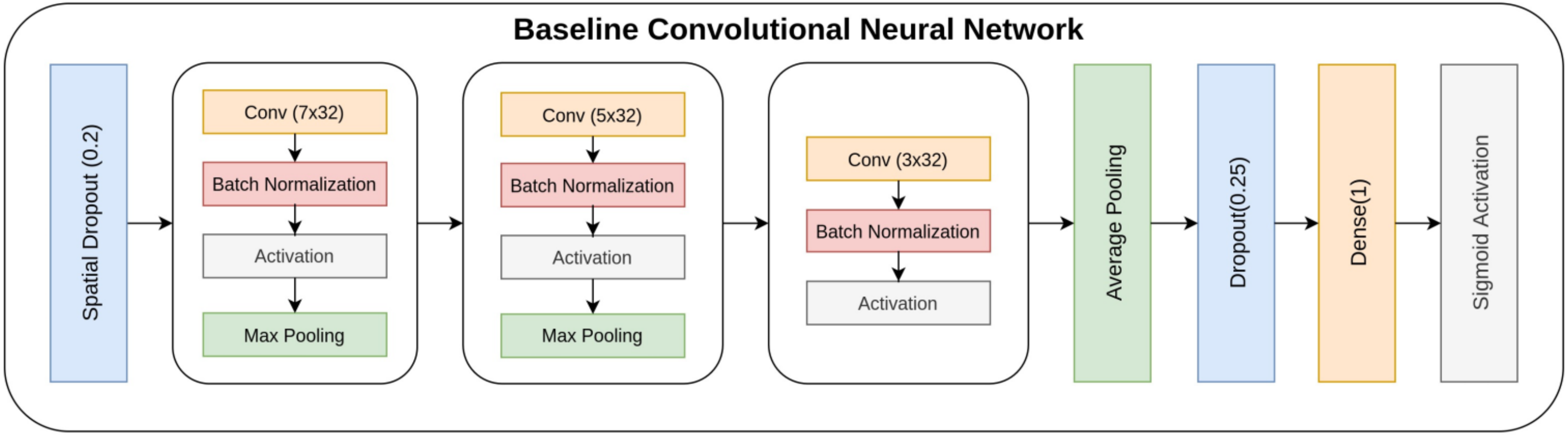
Related Work

- Zhao et al. use a hybrid CNN, LSTM model to achieve 98.6% accuracy.
- Maachi et al. use a 1D CNN to achieve 98.7% accuracy.
- Xia et al. use a deep attention based neural network to achieve 99.07% accuracy.
- Almost all deep learning-based methods use the following processing pipeline.
  - Divide each gait recording into windows.
  - Use a model to classify each window.
  - Aggregate the predictions for each window to get prediction for the source recording.

Model Evaluation

- Cross-Validation(CV) is used to evaluate models when no holdout test set is present, but CV has its disadvantages.
- Extremely large size of models in literature raises doubts of model evaluation strategies used.
- We analize different validation split strategies used in literature with a 10% holdout test set.
  - **Window Level**: Random 10% of all the available windows make up the validation set and the remaining 90% make up the train set.
  - **Within Recording**: Random 10% of windows from each recording make up the validation set and the remaining 90% windows in each recording makeup the train set.
  - **Subject Level**: Windows belonging to 10% of the subjects make up the validation set and windows belonging to the remaining 90% make up the train set.

Model Evaluation

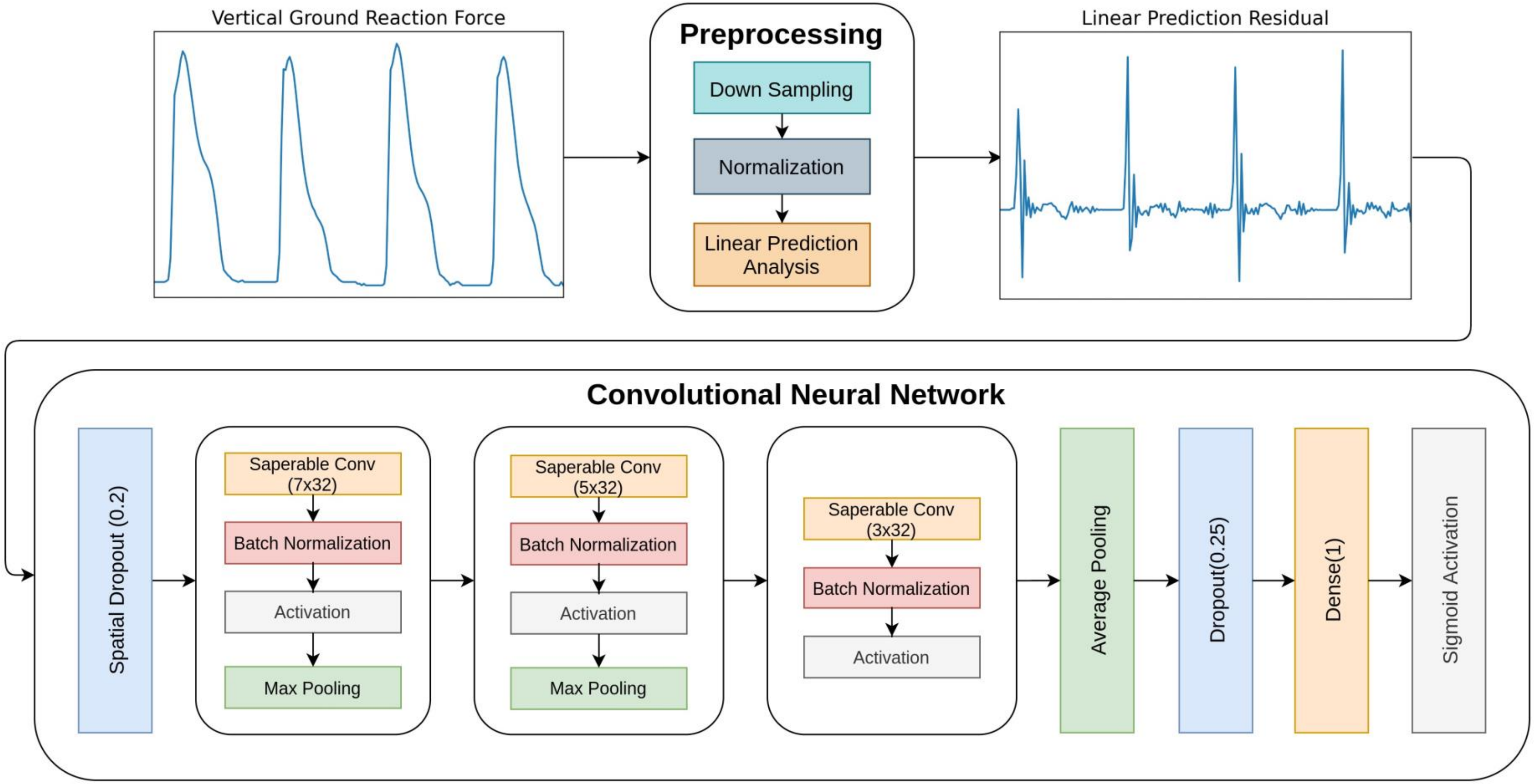


Model Evaluation

- We measure difference between validation and test accuracy to measure data leakage.
- Data leakage may be present in within recording and window level split strategies.
- Subject level saperation between validation splits necessary to correctly validate a model.
- 10-fold CV with a subject level saperation between folds used to evaluate proposed model.

Split Strategy	Train	Validation	Test	Difference (Validation-Test)
Within Recording	**95.9 (0.285)**	**95.9 (0.284)**	74.9 (0.637)	21.0 (0.353)
Window Level	94.6 (0.301)	94.1 (0.308)	74.3 (0.661)	19.8 (0.353)
Subject Level	88.7 (0.387)	74.7 (0.572)	**78.8 (0.580)**	**4.1 (0.008)**

LPGNet Model Architecture



Linear Prediction(LP)

- Mathematical operation where future samples in a time series are estimated as a linear combination of *p* past samples.
- Used to model human voice box in speech compression systems.
- We use it to model gait of a healthy human subject.
- LP Residual is the prediction error that captures deviations from normal gait.
- Residual used as input to a CNN to perform diagnosis.

$$\widehat{x}(n) = -\sum_{i=1}^{p} a(i)x(n-i)$$

$$e(n) = x(n) - \widehat{x}(n)$$

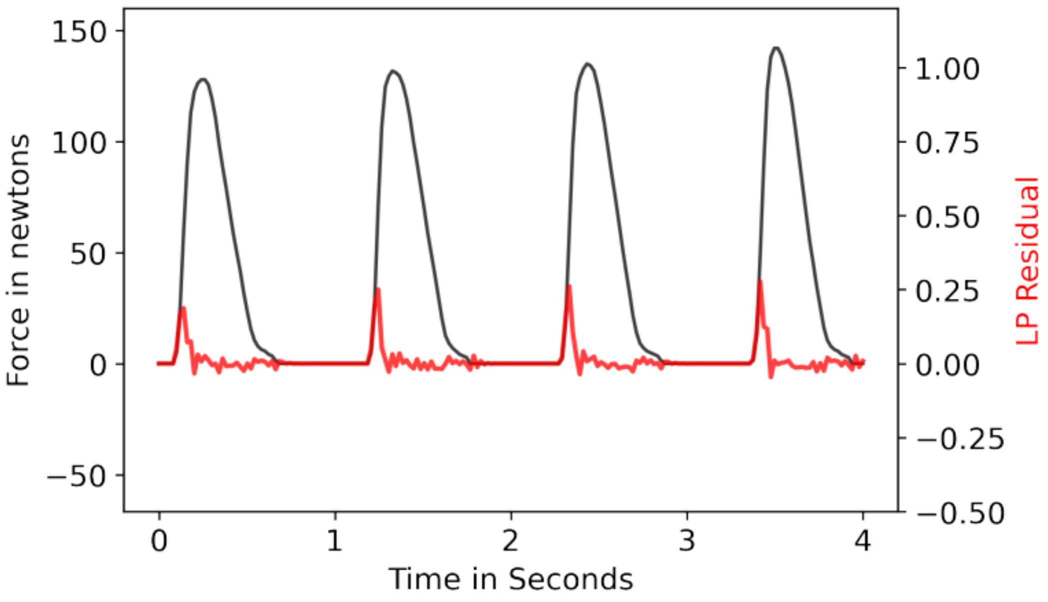
Linear Prediction

- Many methods exist to find coefficients in Linear Predictor.
- The least squares solution to the following system of equations gives optimal coefficients.

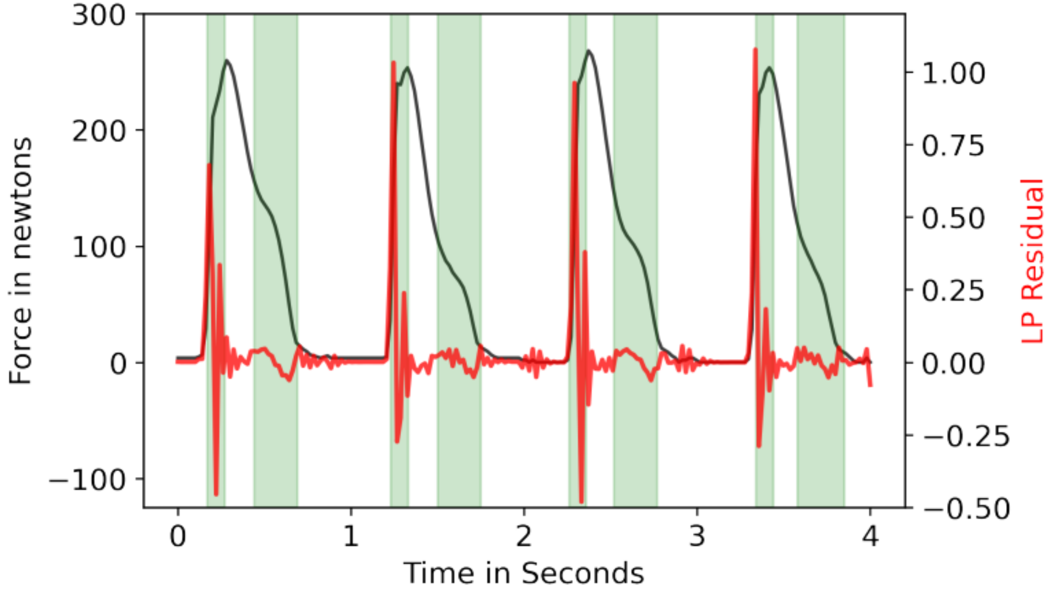
$$Xa = b$$

$$X = \begin{bmatrix} x(1) & 0 & \cdots & 0 \\ x(2) & x(1) & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ x(p+1) & \cdots & \cdots & x(1) \\ \vdots & \vdots & \cdots & \vdots \\ 0 & \cdots & 0 & x(m) \end{bmatrix}, \quad a = \begin{bmatrix} 1 \\ a(1) \\ \vdots \\ a(p) \end{bmatrix}, \quad b = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Linear Prediction Residual.

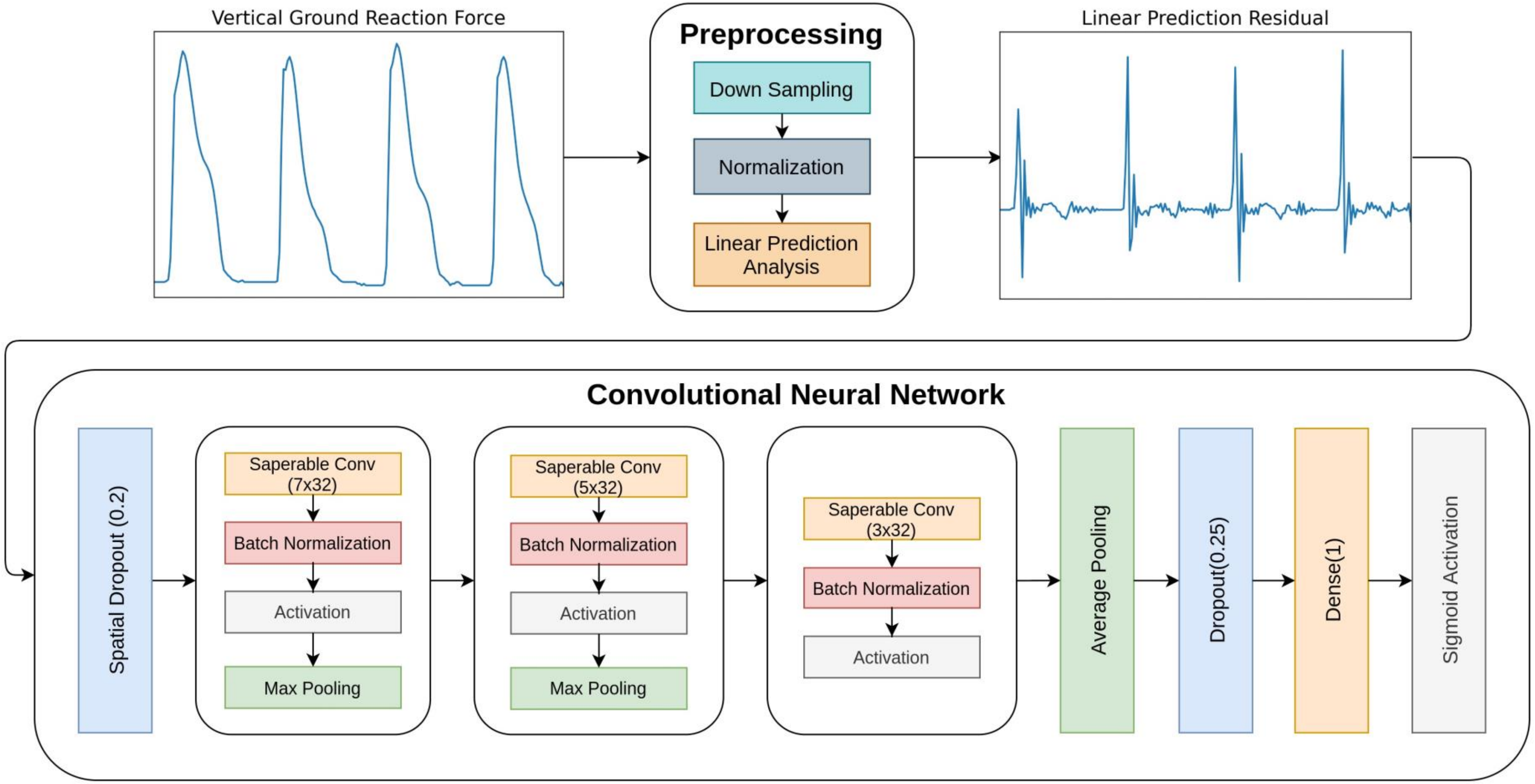


(a) Normal Gait



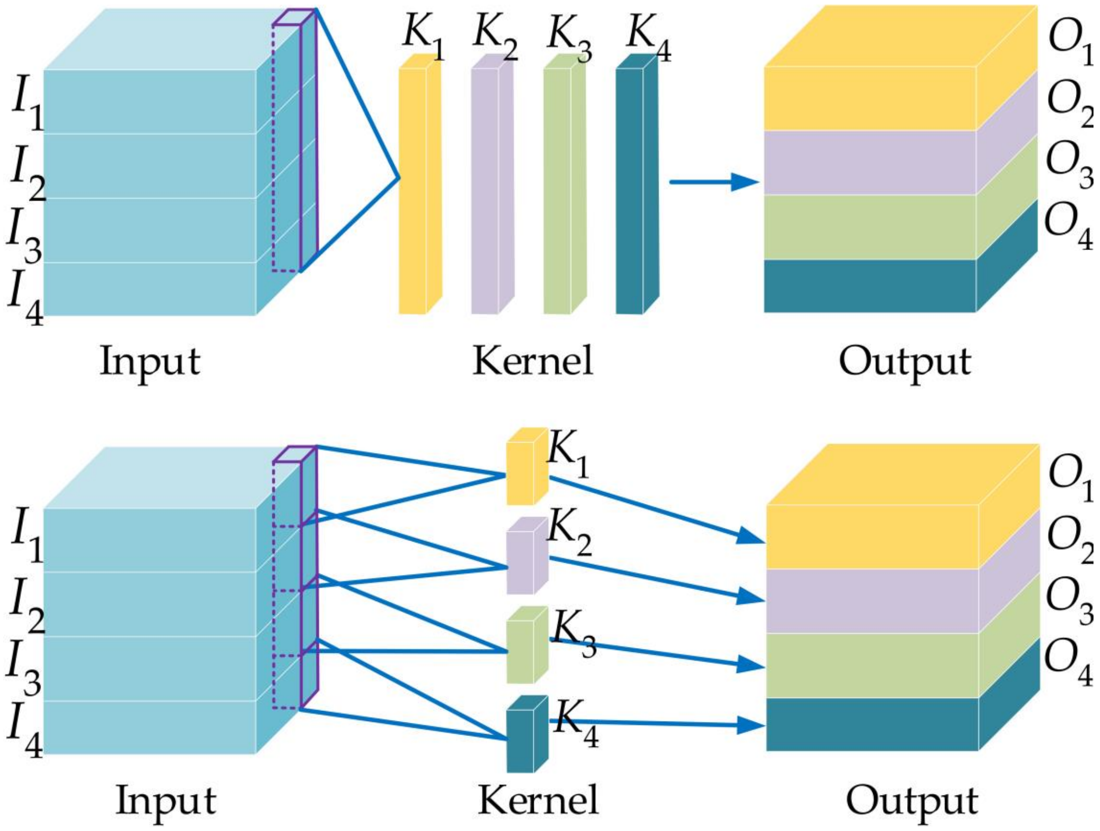
(b) Parkinsonian Gait

LPGNet Model Architecture



Saperable Convolutions

- A more parameter efficient version of Convolutions



Preprocessing

- To remove unwanted artefacts that may comeup due to downsampling the raw signal is first filtered with a moving average filter of order 2.
- Each recording is downsampled to 50Hz and normalized to unit variance.
- Each recording is then divided into overlapping windows of 100 samples each representing 2 seconds each.

Training

- LP coefficients are obtained by solving for the least squares solution.
- CNN training is done in two stages.
  - Window level training of the entire network.
  - Recording level training of the last perceptron layer where CNN weights are frozen.
- Binary crossentropy with label smoothing was used as the loss function to optimize.
- The network was regularized with dropout and L2 Regularization.
- At test time we pass the entire processed recording at once to obtain a prediction.

Results

- Proposed LPGNet faster, smaller and more accurate than the current SOTA.
- Possible reasons for speedup
  - Model takes in entire recording at once avoiding overhead.
  - Use of saperable convolutions.
  - Use of LP residual that enables us to downsample without losing performance.
  - Fixing the model evaluation strategy which leads to an optimal model for the data.

Method	AUC	F1 Score	Accuracy	Inference Time (ms)	Parameters
LPGNet	$\mathbf{91.7 \pm 9.4}$	$\mathbf{93.2 \pm 3.6}$	$\mathbf{90.3 \pm 5.8}$	**9.3ms**	4933
Ablation	90.4 ± 8.1	91.2 ± 4.9	87.6 ± 6.7	13.4ms	**4735**
Baseline	87.6 ± 11.4	88.7 ± 6.9	83.6 ± 9.7	20.6ms	16001
1D-ConvNet[5]	86.7 ± 10.3	88.2 ± 6.8	82.5 ± 10.1	195.1ms	445841

Summary

- Compared various model evaluation strategies used in the literature to classify gait patterns for Parkinson's Diagnosis to establish guidelines for future research.
- Proposed LPGNet a novel model for diagnosis of Parkinson’s disease from gait patterns that is orders of times faster and smaller while outperforming current methods in literature.
  - Proposed method is 21 times faster with 99% lesser parameters than SOTA.
- Performed an ablation study to verify the significance of the linear prediction residuals.