PARKINSON'S DISEASE DIAGNOSIS USING DEEP LEARNING

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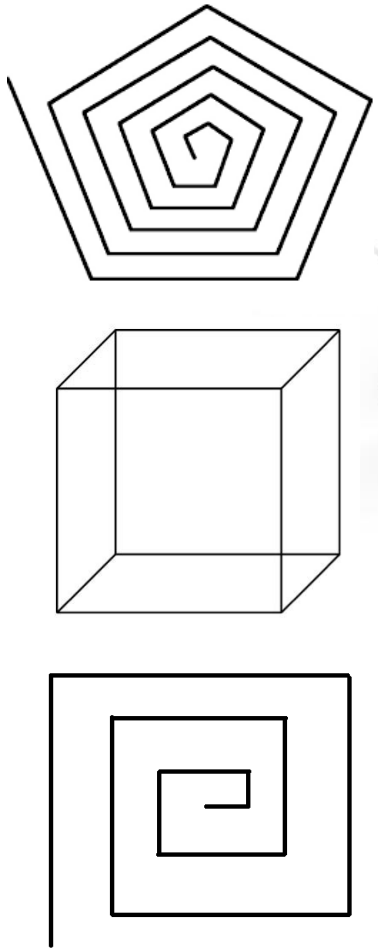
SUPERVISORS: DR MICHAEL LONES & DR MARTA VALLEJO

Head lines

- Data Acquisition
- The project story
- Project Objectives
- Experiments
- Implementation Work flow
  - ✓Data processing step
  - ✓Classification step
  - ✓Evaluation
  - ✓Discuss the best approach
  - ✓Results
- Future work

Data Acquisition



The Project Story

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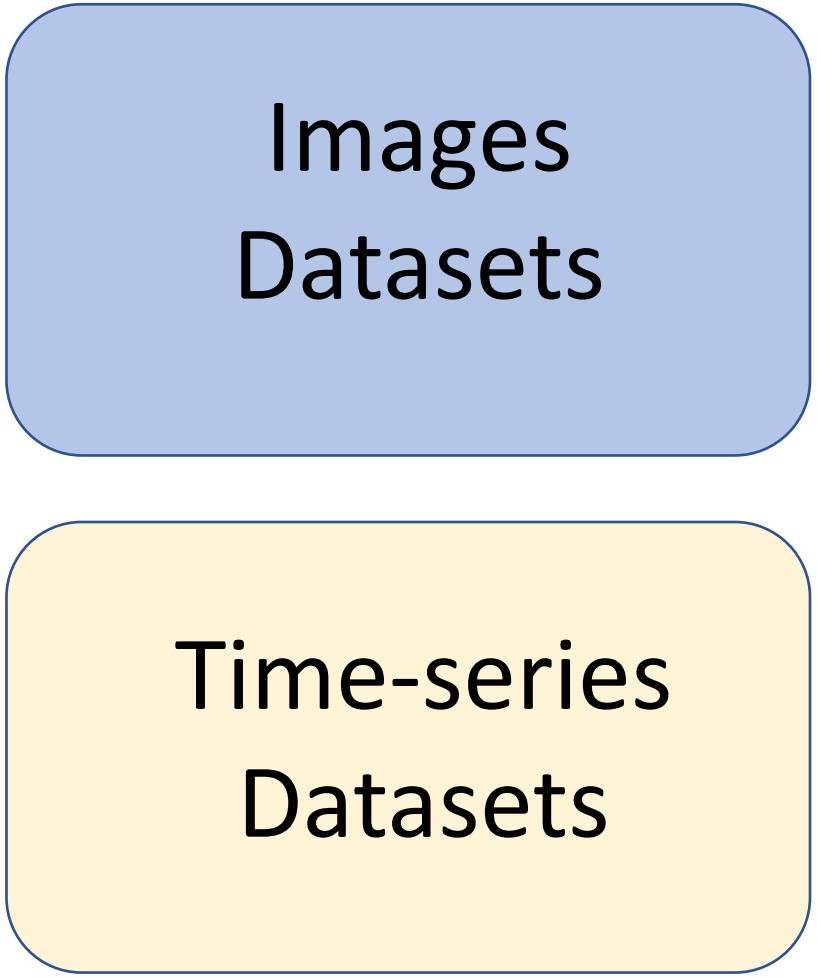
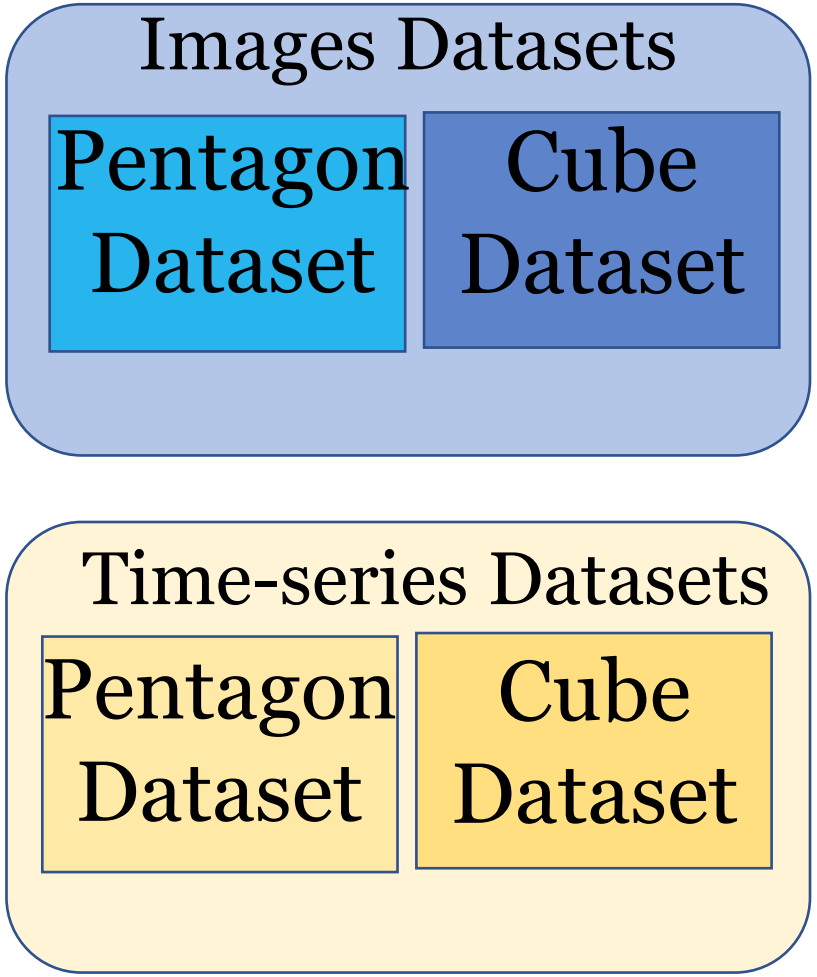


Fig 1 Data sets

The Project Story



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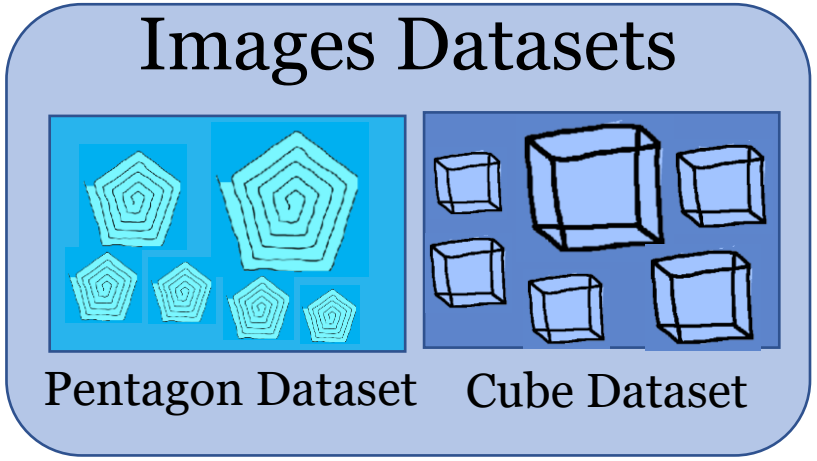
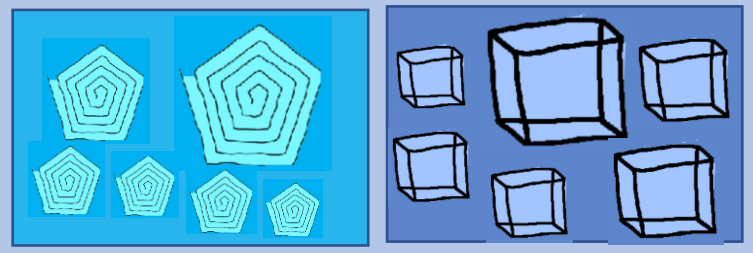


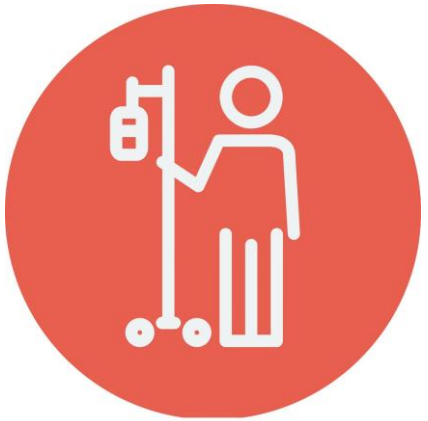
Fig 1 Data sets

The Project Story

Images Datasets



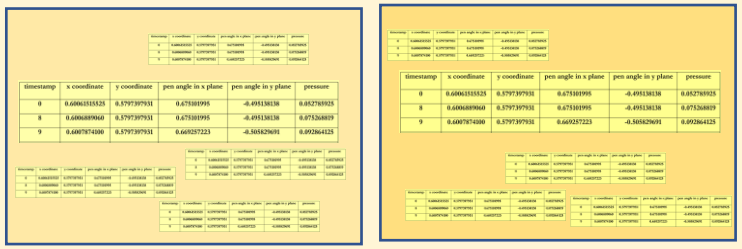
Pentagon Dataset Cube Dataset



58 Patients

29 Healthy

Time-series Datasets



Pentagon Dataset Cube Dataset

Datasets	Shortest sample	Longest sample
Cube	1268	15968
Pentagon	2662	25532

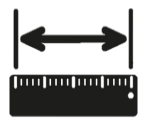
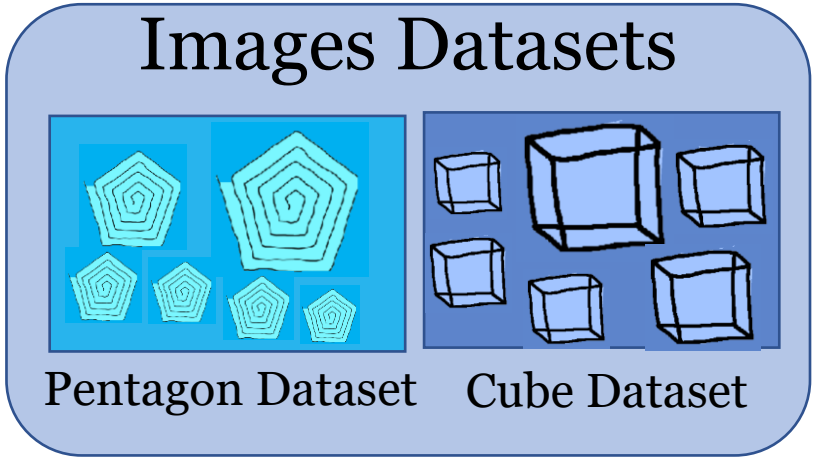


Fig 1 Data sets

The Project Story

Convolutional neural networks

Recurrent neural networks



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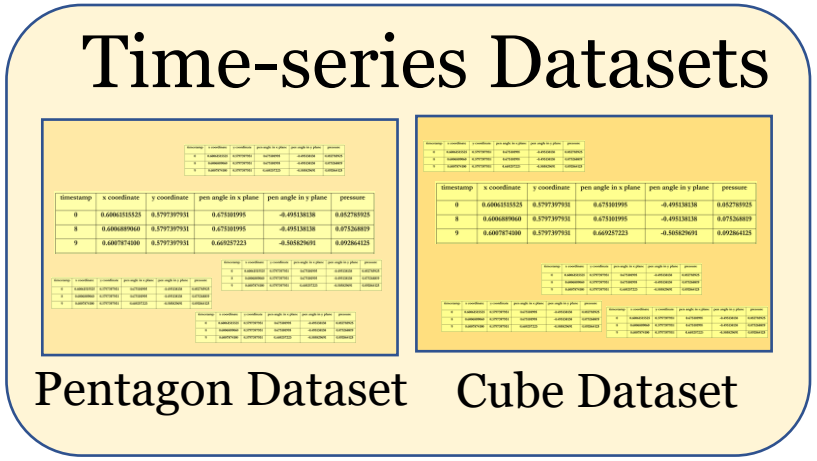

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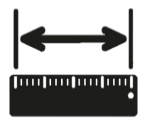

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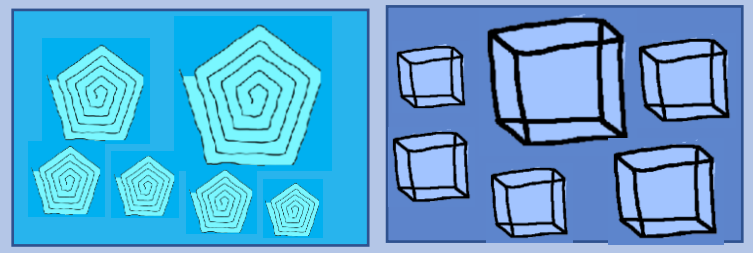

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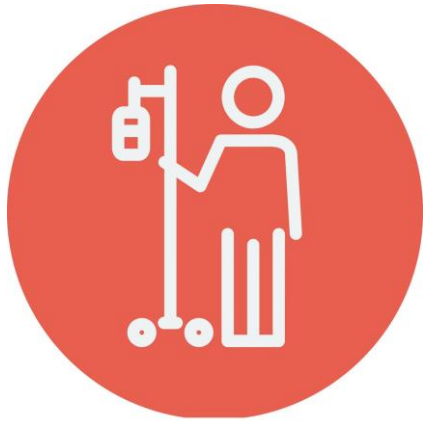

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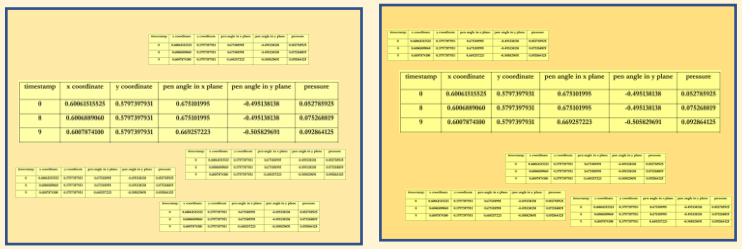
Time-series Datasets



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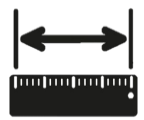

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Convolutional neural networks

Recurrent neural networks

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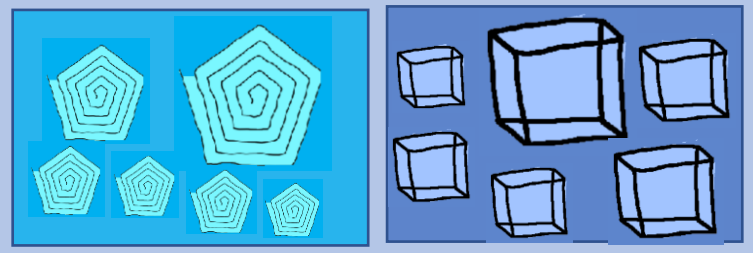

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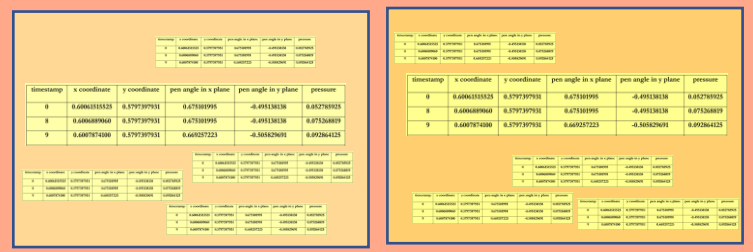

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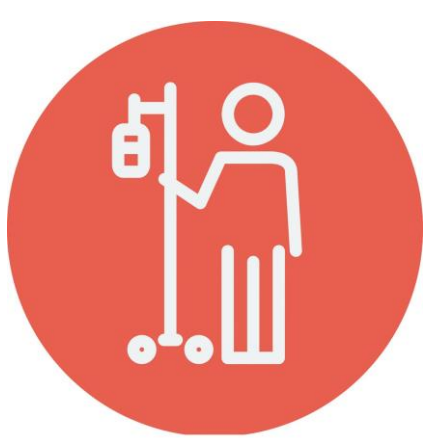

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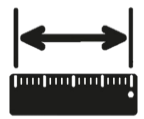

Fig 1 Data sets

The Project Story

Convolutional neural networks

Recurrent neural networks

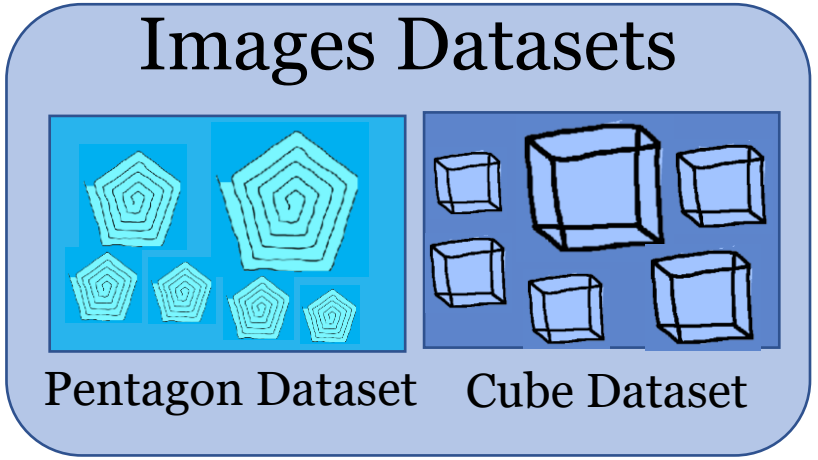

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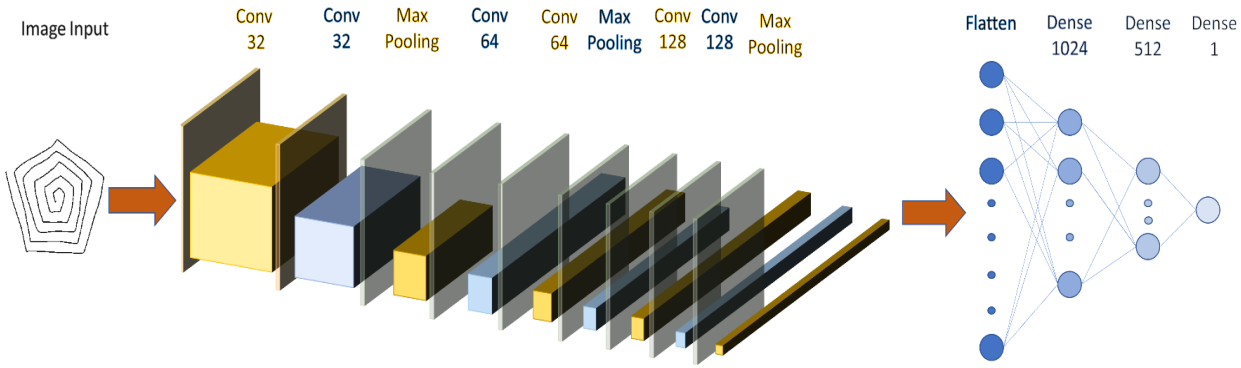
Fig 1 Data sets

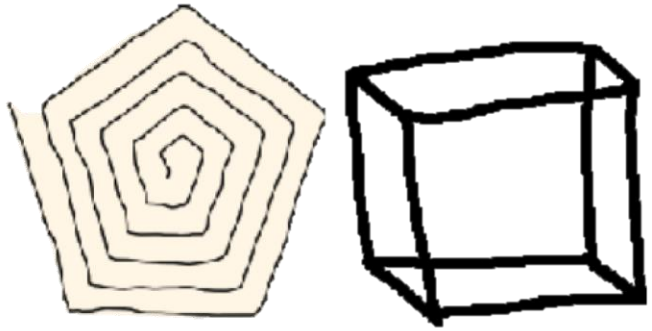
Project Objectives

1. Examine which of the image datasets (each one related to a different PD drawing test) are more useful for training predictive models.
2. Investigate which of the time series datasets are more useful for training predictive models.
3. Explore whether imaging datasets or time series datasets are more effective as a basis for discrimination.

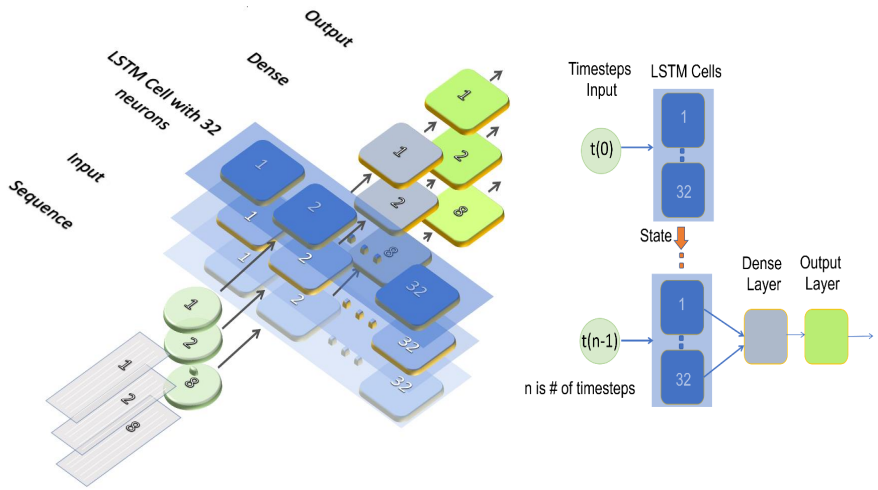
Experiments

- **Convolutional Neural Networks Experiments**





- **Recurrent Neural Networks Experiments**



timestamp	x coordinate	y coordinate	pen angle in x plane	pen angle in y plane	pressure
0	0.60061515525	0.5797397931	0.675101995	-0.495138138	0.052785925
8	0.6006889060	0.5797397931	0.675101995	-0.495138138	0.075268819
9	0.6007874100	0.5797397931	0.669257223	-0.505829691	0.092864125

Experiments

CNN Experiments

- Experiments with imbalanced datasets.
  - 32x32 pixels
  - 64x64 pixels
  - 128x128 pixels
- Experiments with balanced datasets
  - 32x32 pixels
  - 64x64 pixels
  - 128x128 pixels

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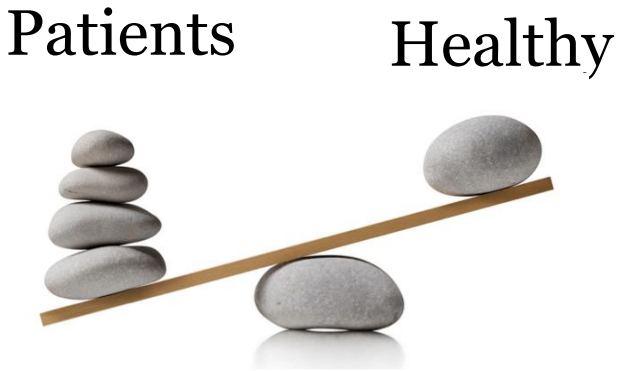

Experiments

CNN Experiments

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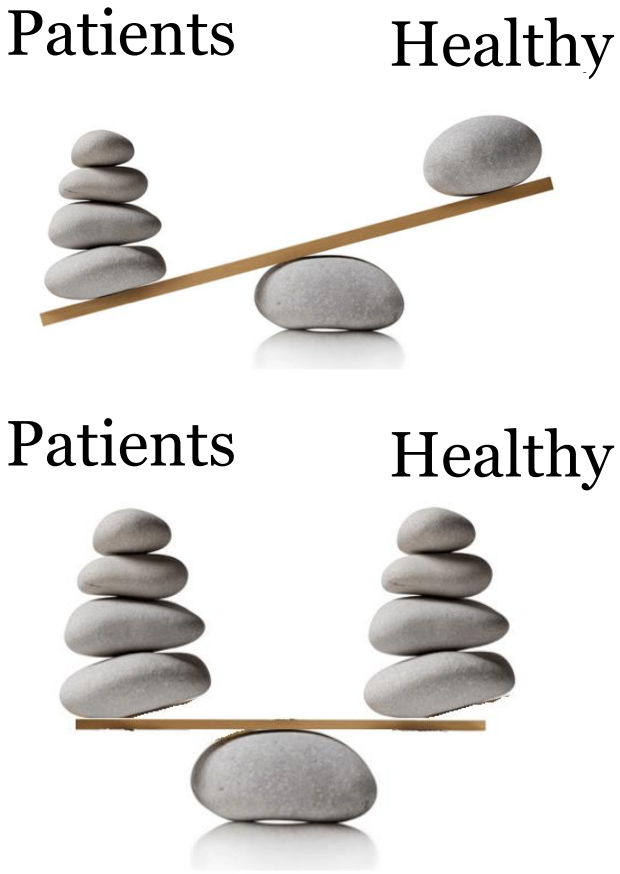
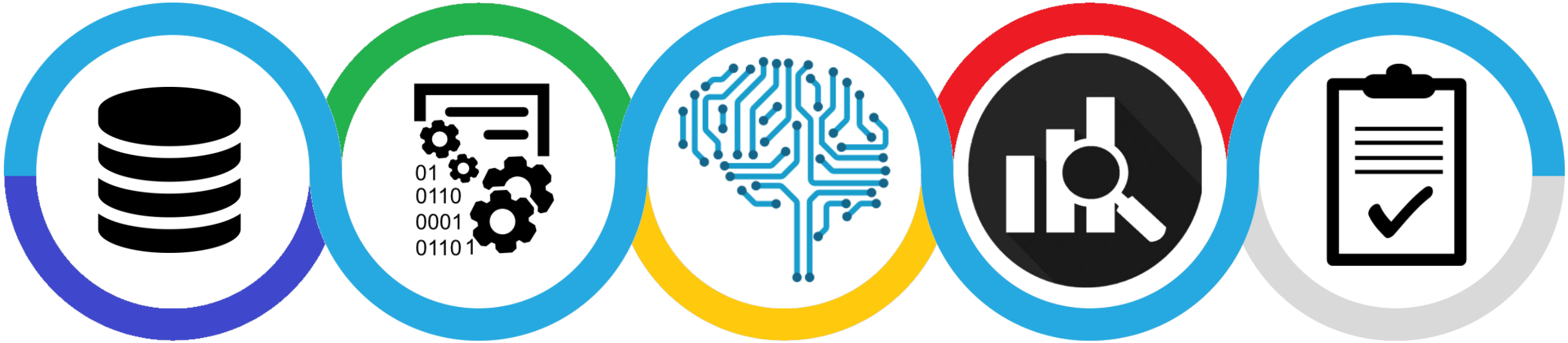


Fig 2 Imbalance VS balance dataset

Implementation Work Flow



Original dataset Data processing Classification step Evaluation step Results

Fig 3 Implementation Work Flow

Implementation Work Flow
Convolutional Neural Networks

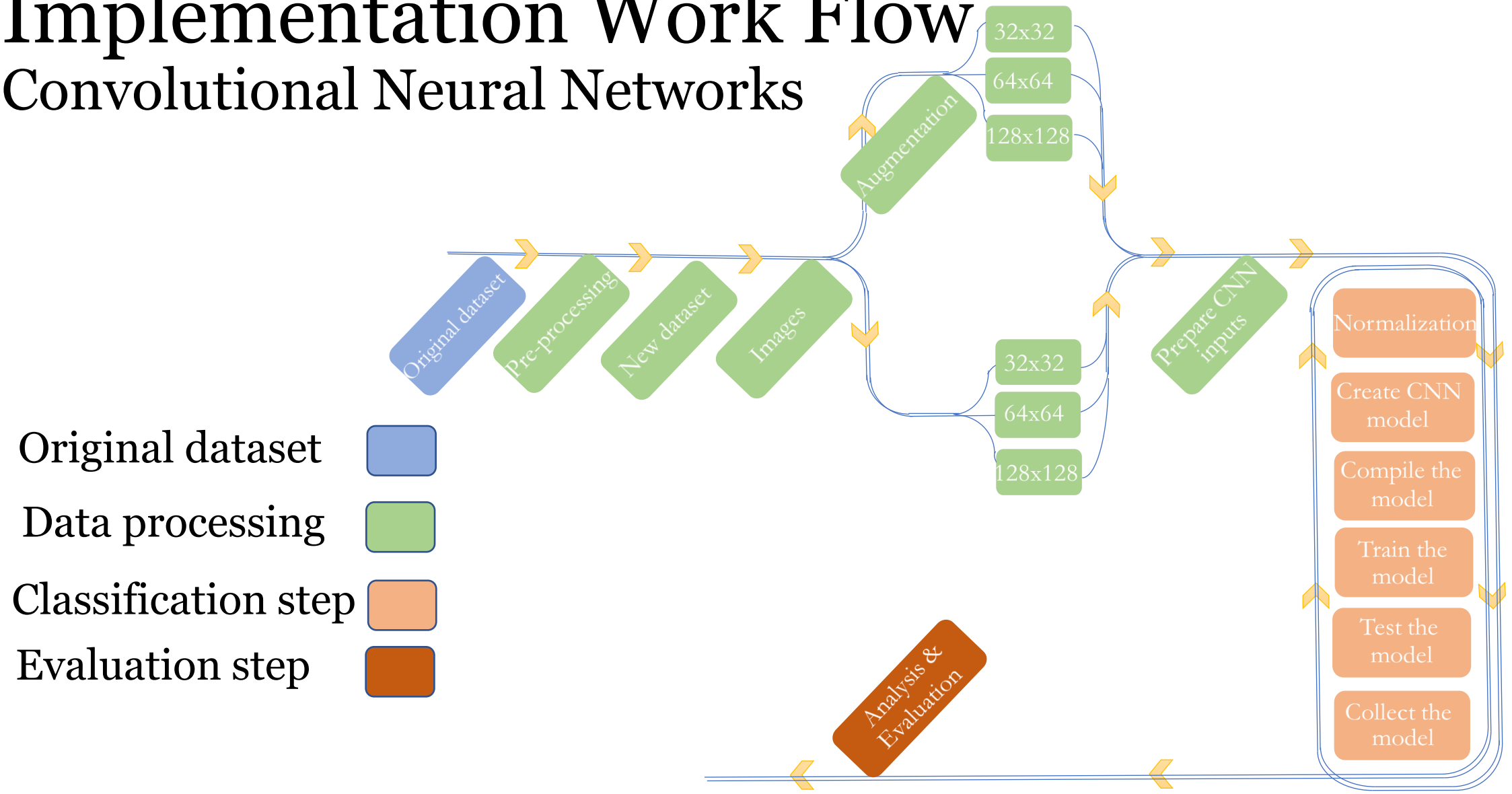
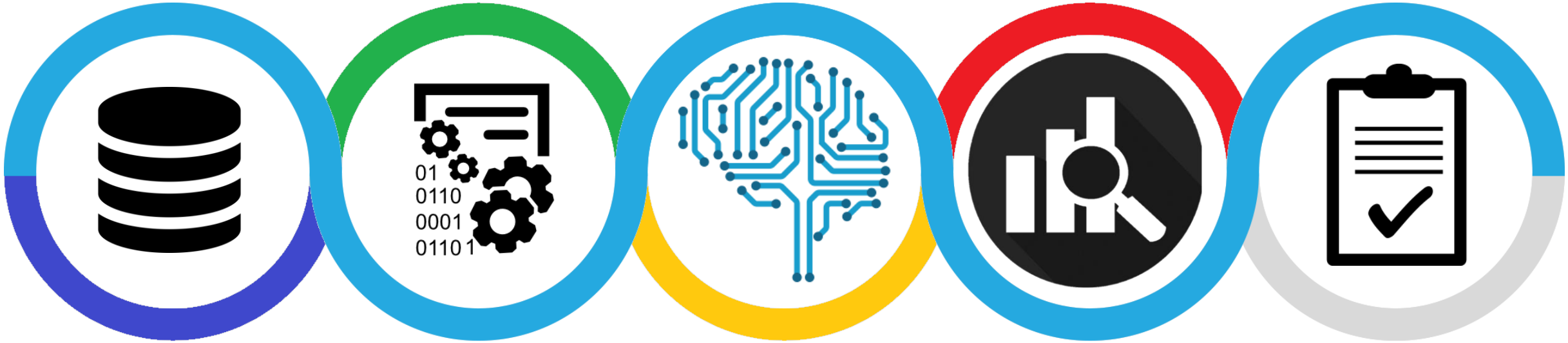


Fig 4 CNN-based experiments' workflow

Implementation Work Flow



Original dataset | Data processing | Classification step | Evaluation step | Results

Data Processing
Convolutional Neural Networks

- Data pre-processing
- Image processing
- Data preparation

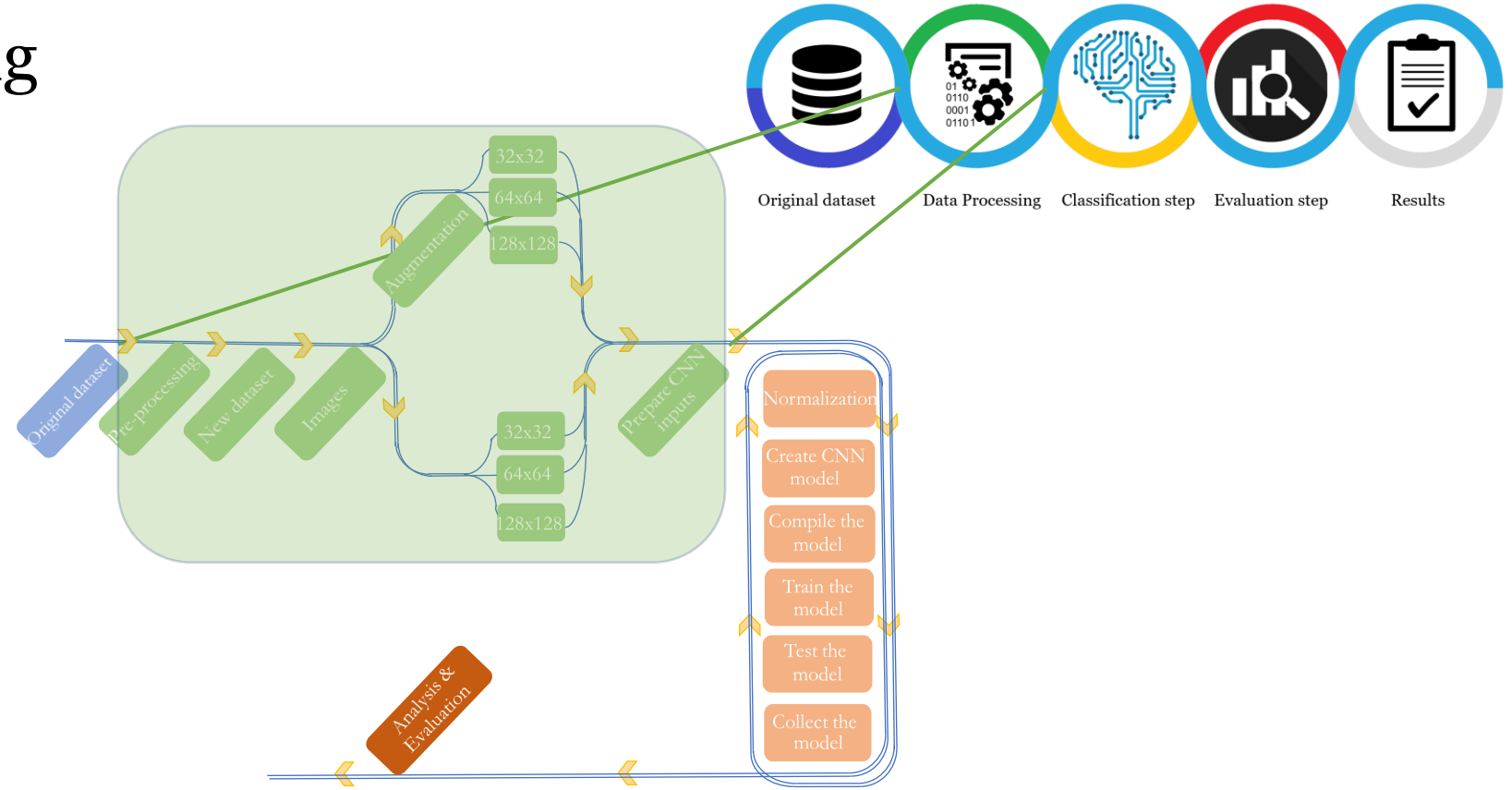


Fig 5 CNN-based experiments' workflow focused on data processing part

Data Processing
Convolutional Neural Networks

- Data Pre-processing
  - ✓Data cleansing
  - ✓Deleting the undesirable features

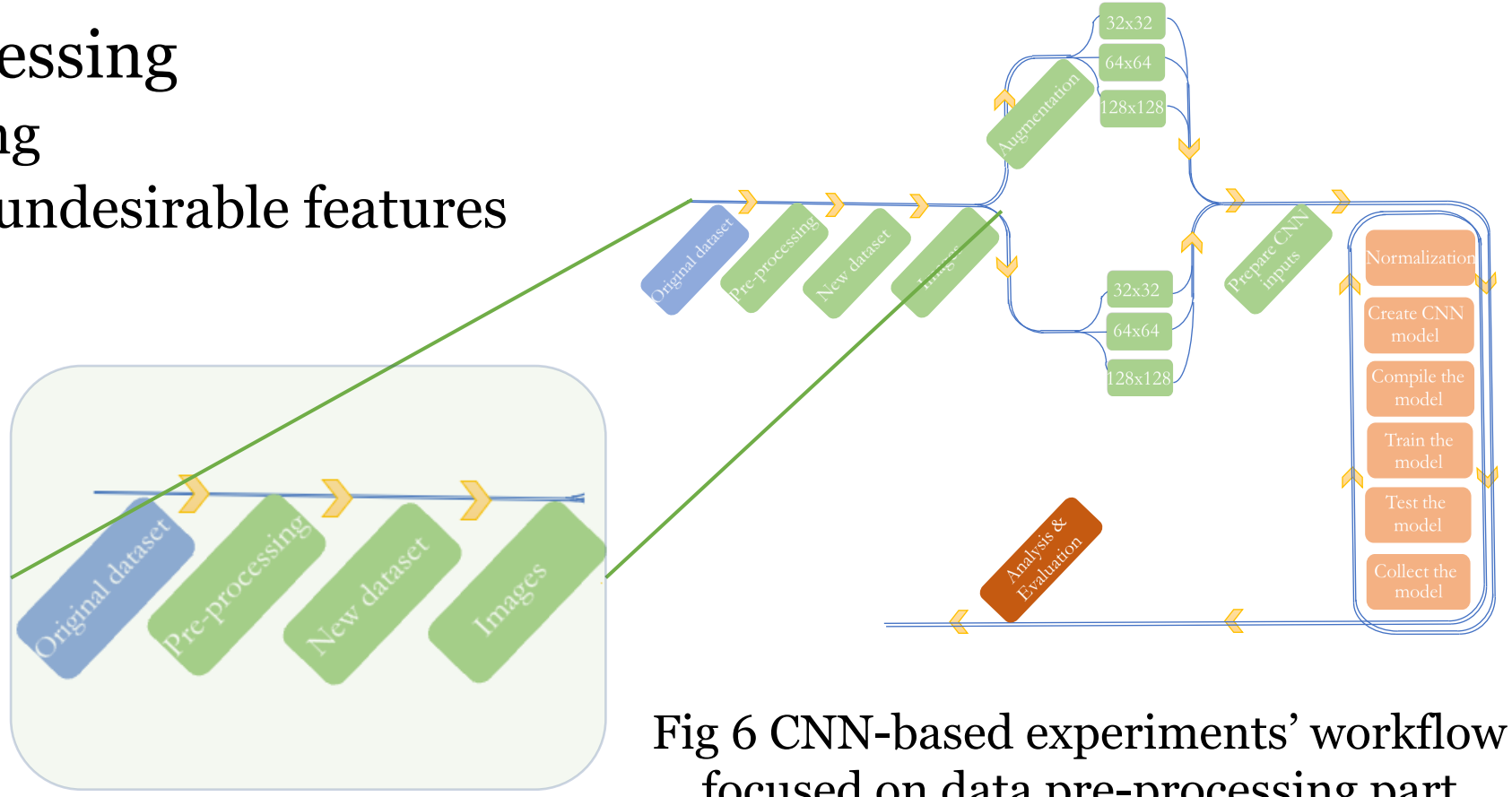


Fig 6 CNN-based experiments' workflow focused on data pre-processing part

Data Processing
Convolutional Neural Networks

- Image processing
  - ✓Augmentation
  - ✓Resizing Images
  - ✓Normalisation

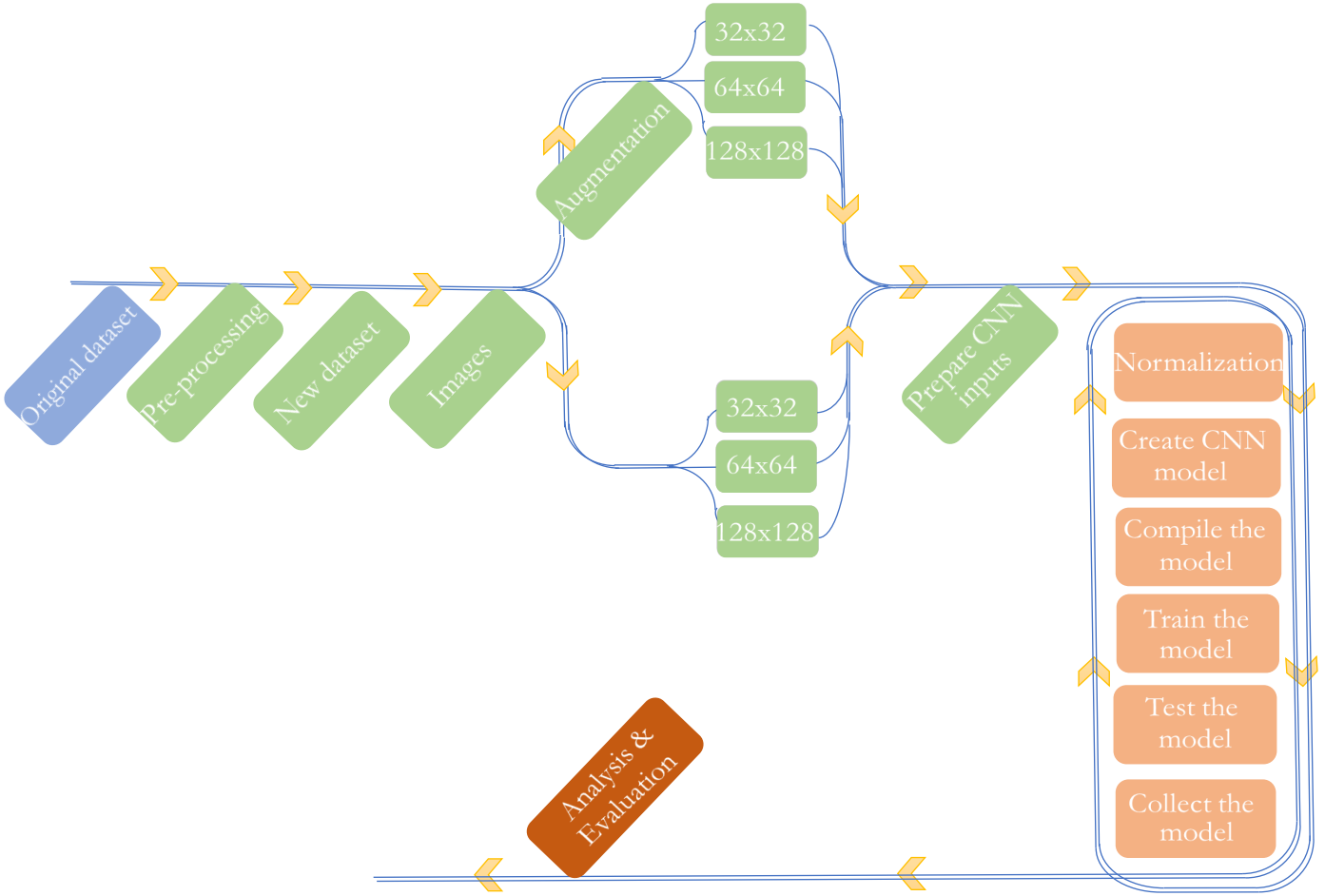
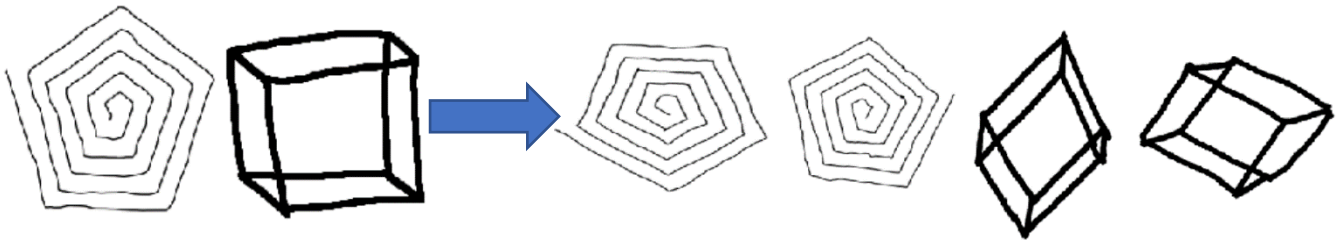


Fig 7 CNN-based experiments' workflow focused on image processing part

Data Processing
Convolutional Neural Networks

- Image processing
  - ✓Augmentation
  - ✓Resizing Images
  - ✓Normalisation



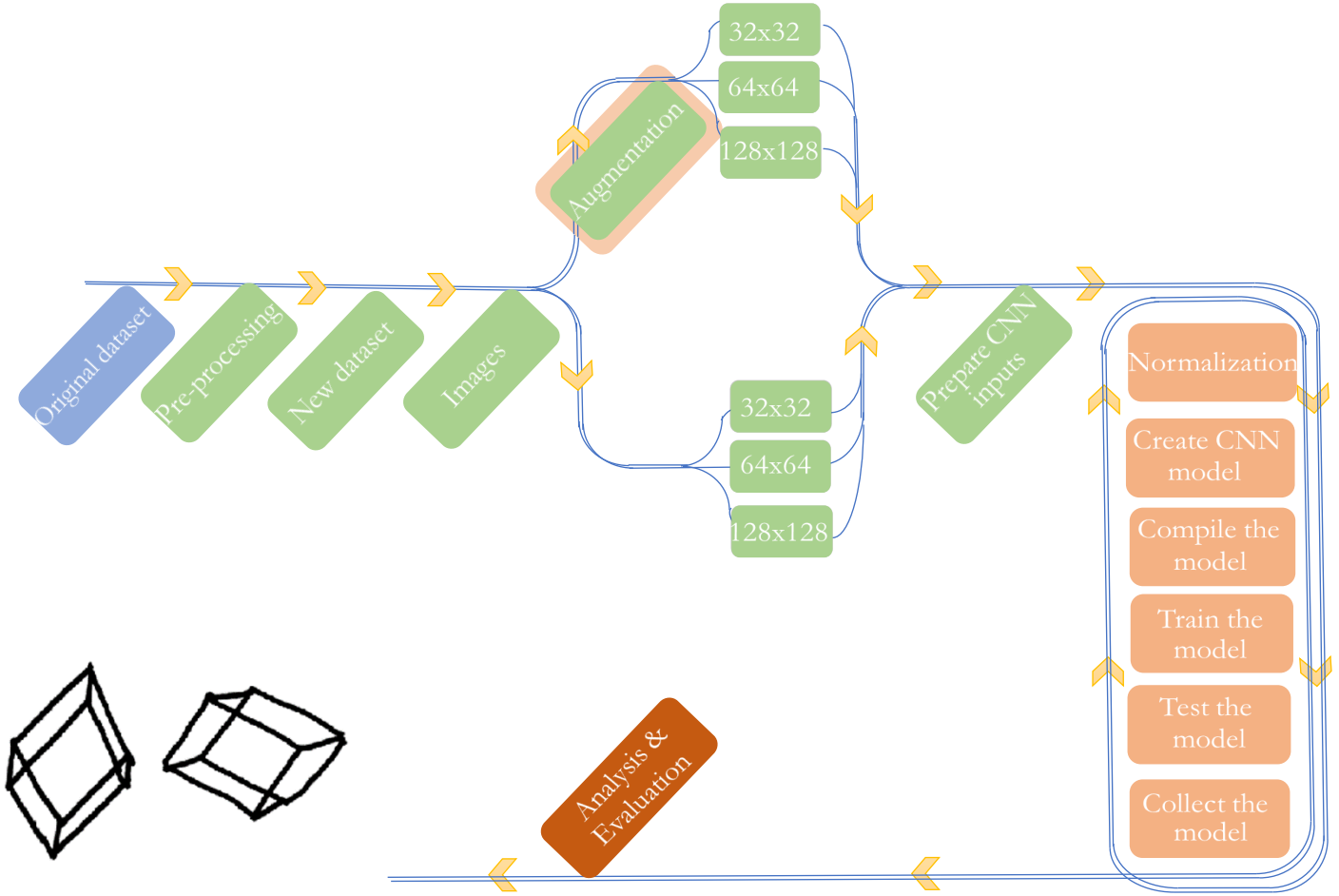
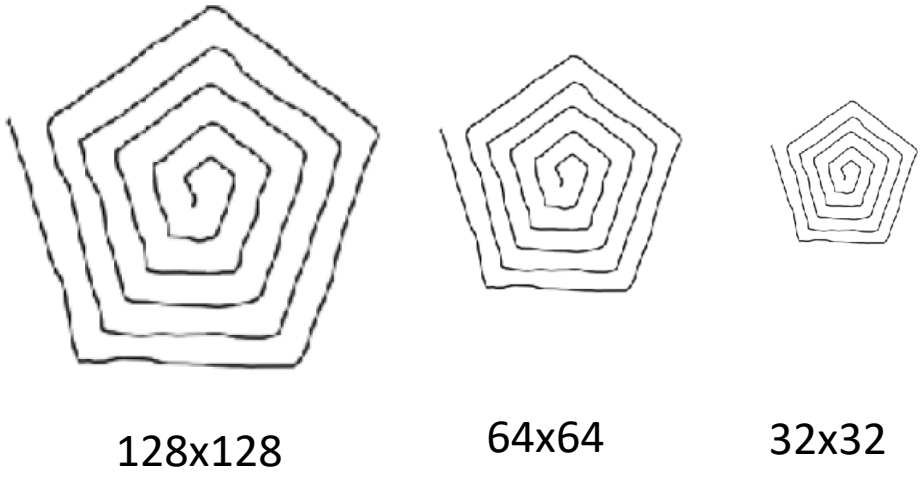


Fig 7 CNN-based experiments' workflow focused on image processing part

Data Processing
Convolutional Neural Networks

- Image processing
  - ✓Augmentation
  - ✓Resizing Images
  - ✓Normalisation



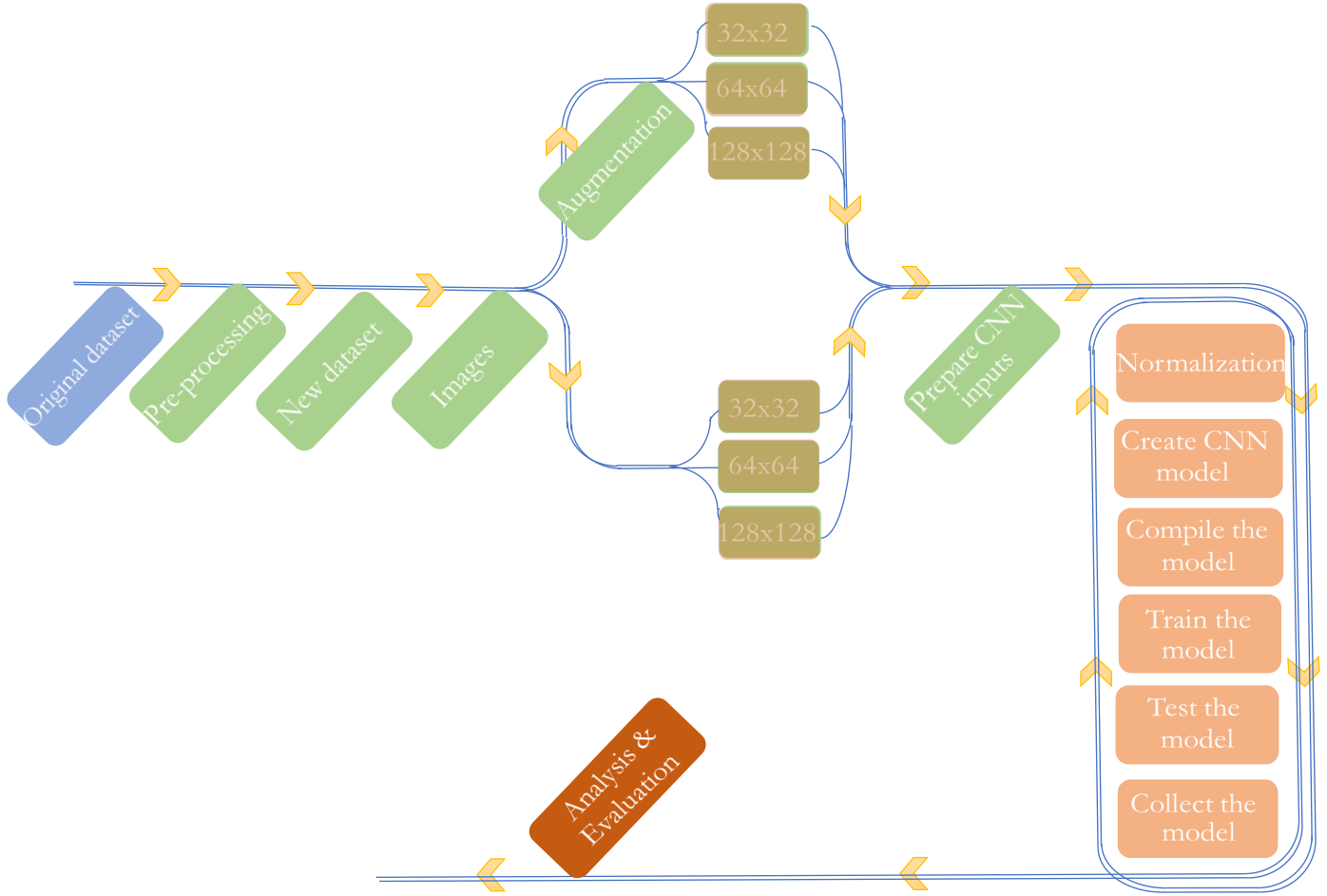


Fig 7 CNN-based experiments' workflow focused on image processing part

Data Processing
Convolutional Neural Networks

- Image processing
  - ✓Augmentation
  - ✓Resizing Images
  - ✓Normalisation

[0 → 255] values → [-1 → 1] values

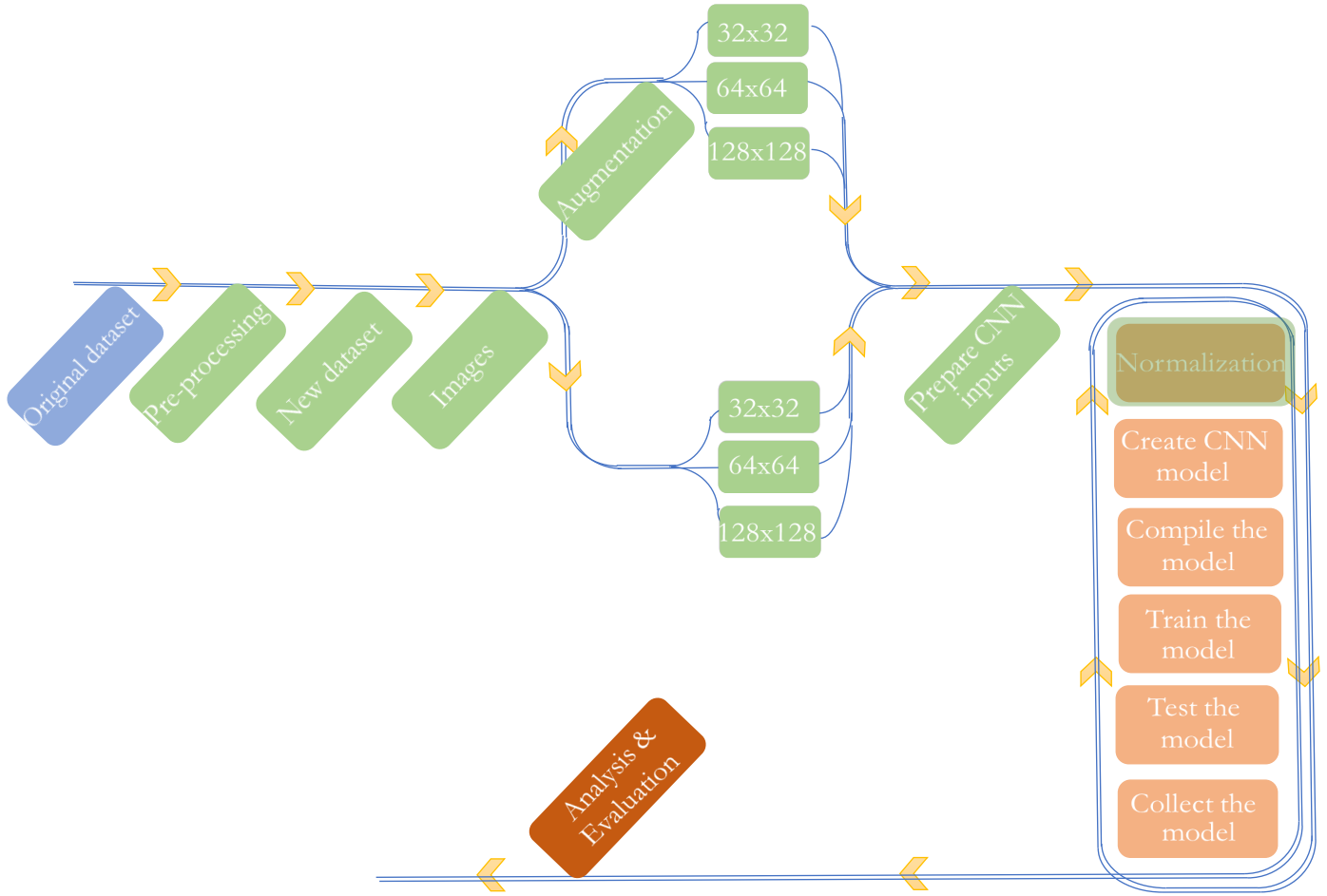


Fig 7 CNN-based experiments' workflow focused on image processing part

Data Processing
Convolutional Neural Networks

- Data preparation(also called data wrangling)
  - ✓Put CNN input in the correct format.
  - ✓Divide the datasets into 90% training & validation and 10% testing sets.

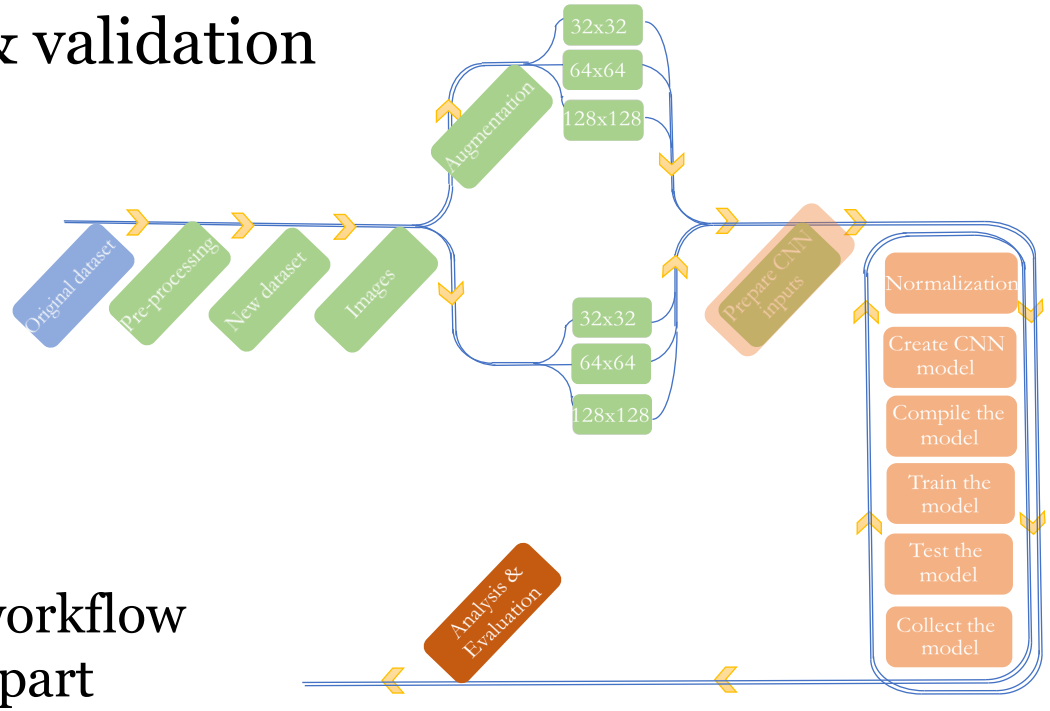
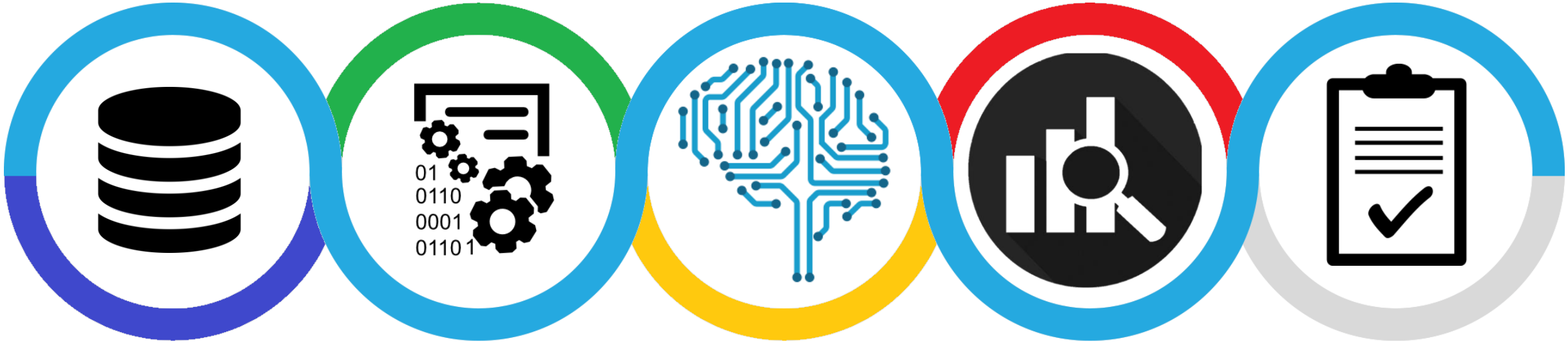


Fig 8 CNN-based experiments' workflow focused on data preparation part

Implementation Work Flow



Original dataset | Data processing | Classification step | Evaluation step | Results

Classification step
Convolutional Neural Networks

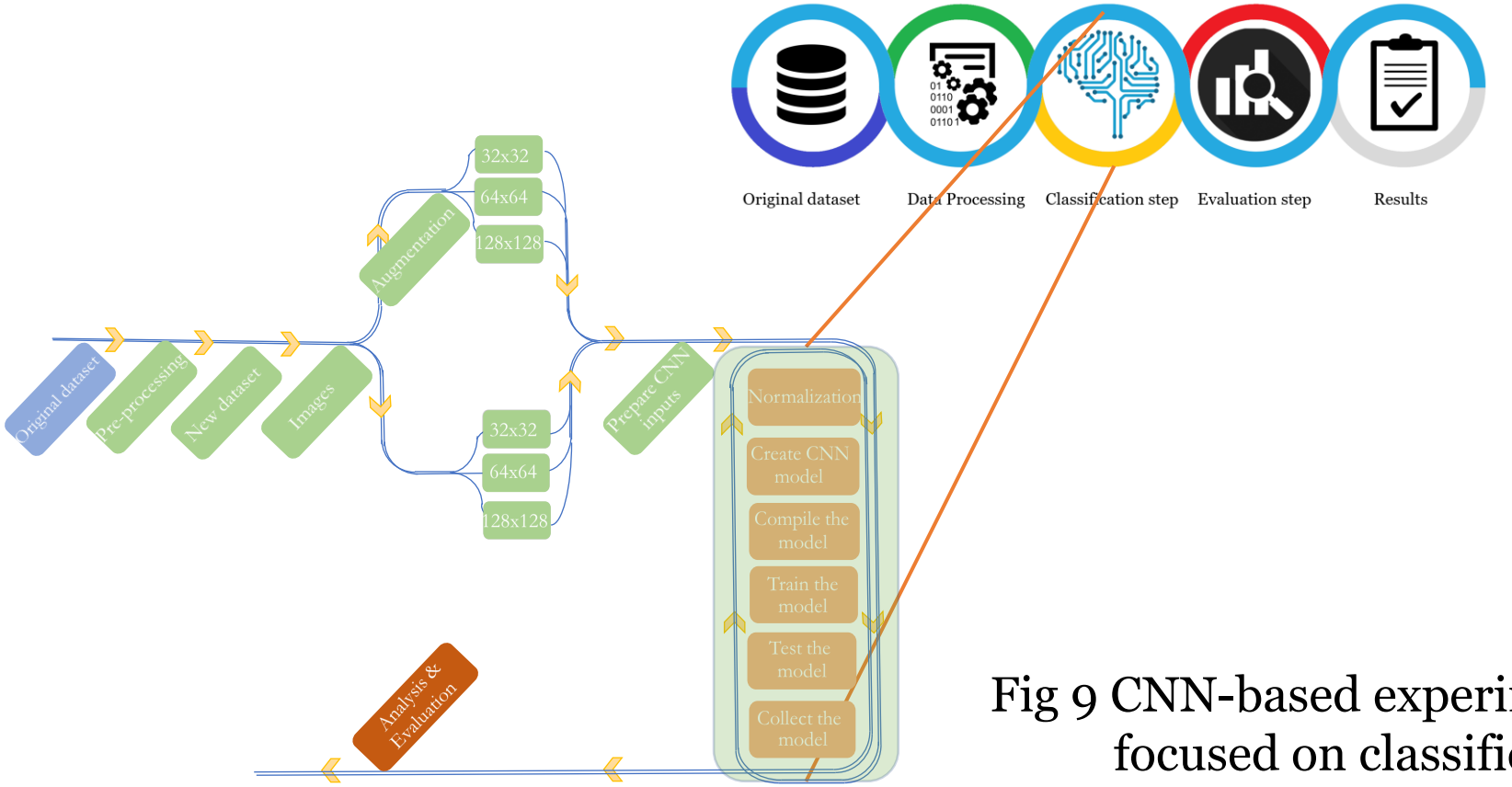


Fig 9 CNN-based experiments' workflow focused on classification part

Classification step
Convolutional Neural Networks

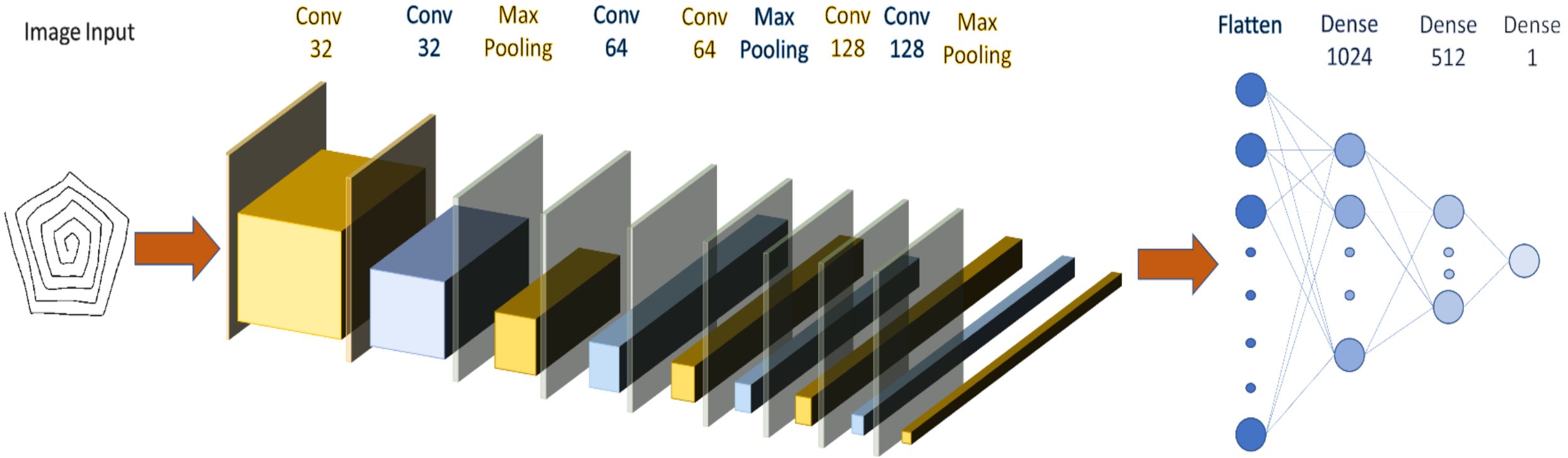
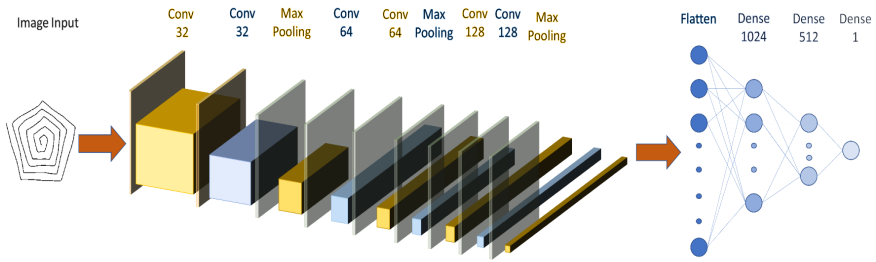


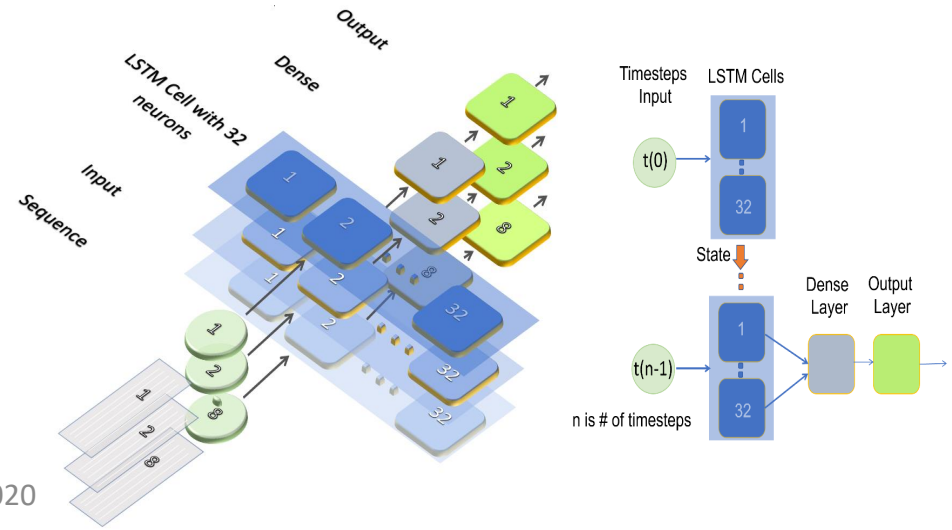
Fig 10 The Proposed CNN Architecture

Experiments

- **Convolutional Neural Networks Experiments**



- **Recurrent Neural Networks Experiments**



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9	0.6007874100	0.5797397931	0.669257223	-0.505829691	0.092864125

Experiments

RNN Experiments

- Experiments without zero-pressure consideration.
- Experiments with zero-pressure consideration.

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RNN Experiments

- Experiments without zero-pressure consideration.
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RNN Experiments

- Experiments without zero-pressure consideration.

- Experiments with zero-pressure consideration.

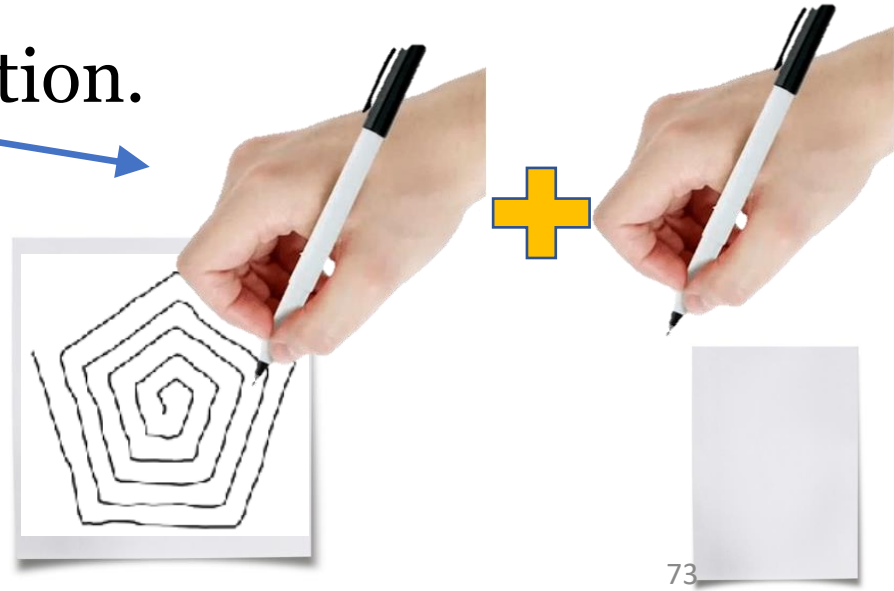
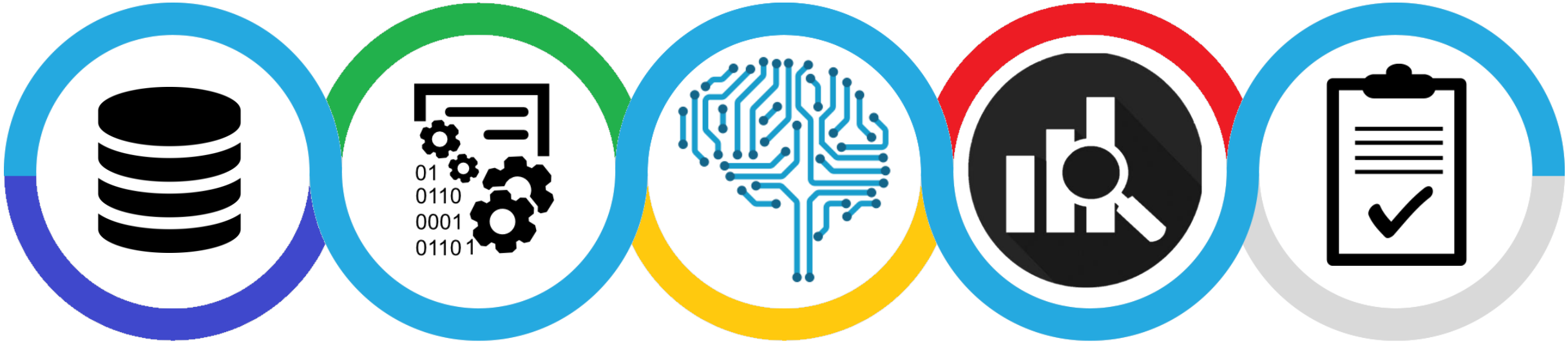


Fig 11 without zero-pressure VS with zero-pressure

Implementation Work Flow



Original dataset Data processing Classification step Evaluation step Results

Implementation Work Flow
Recurrent Neural Networks

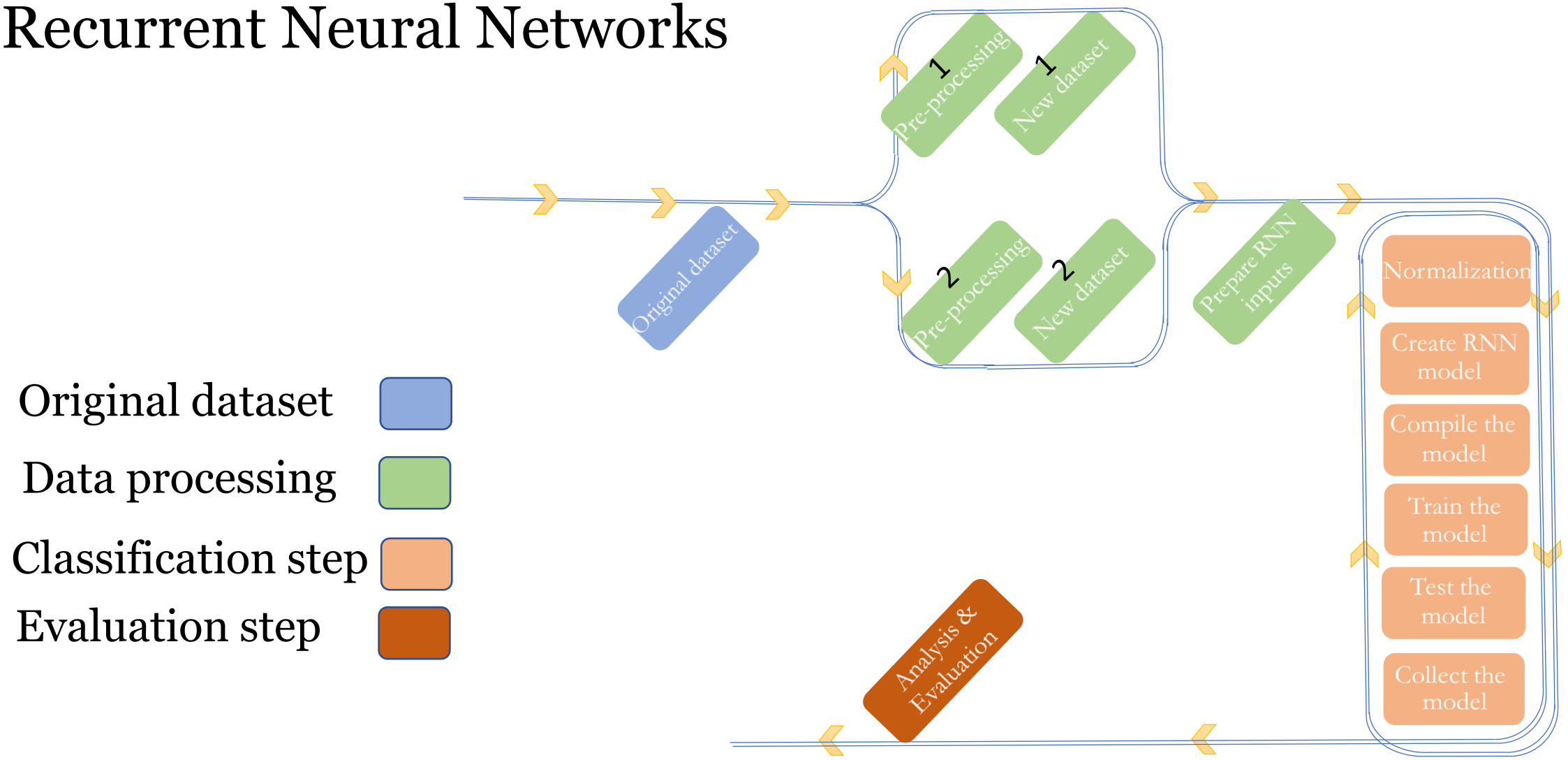
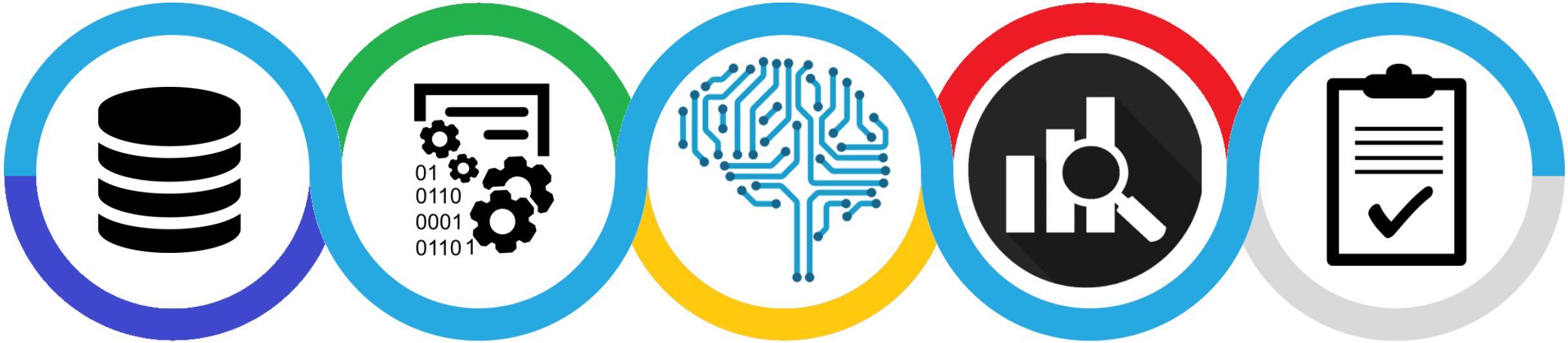


Fig 12 RNN-based experiments' workflow

Implementation Work Flow



Original dataset | Data processing | Classification step | Evaluation step | Results

Data Processing
Recurrent Neural Networks

- Data pre-processing
- Data preparation

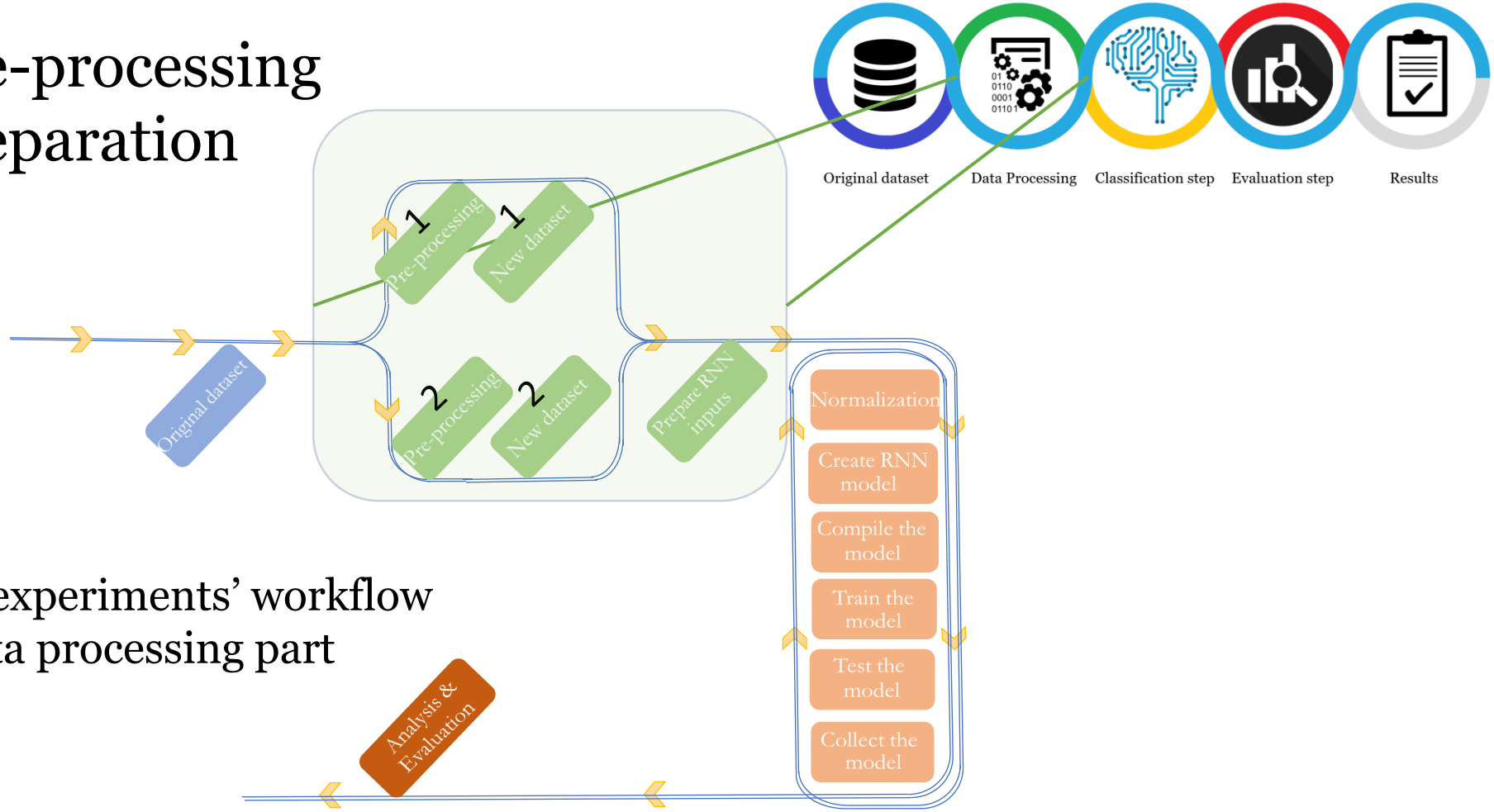


Fig 13 RNN-based experiments' workflow focused on data processing part

Data Processing
Recurrent Neural Networks

- Data Pre-processing
  - ✓Data cleansing
  - ✓Deleting the undesirable features

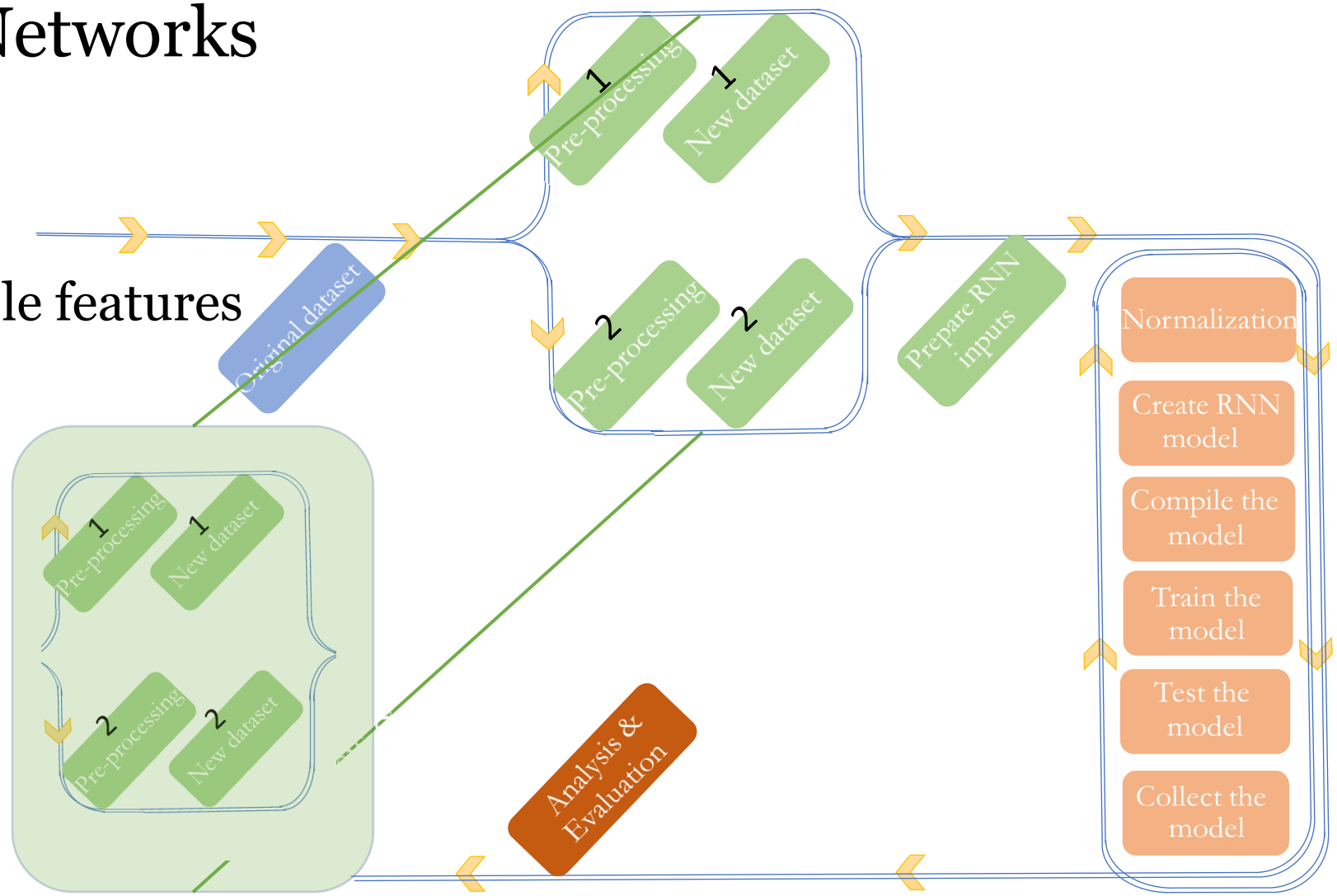


Fig 14
RNN-based experiments' workflow focused on data pre-processing part

Data Processing
Recurrent Neural Networks

- Data preparation(also called data wrangling)
  - ✓Put RNN input in the correct format.
  - ✓Zero-padding to make all samples the same length.
  - ✓Divide the datasets into 90% training & validation and 10% testing sets.

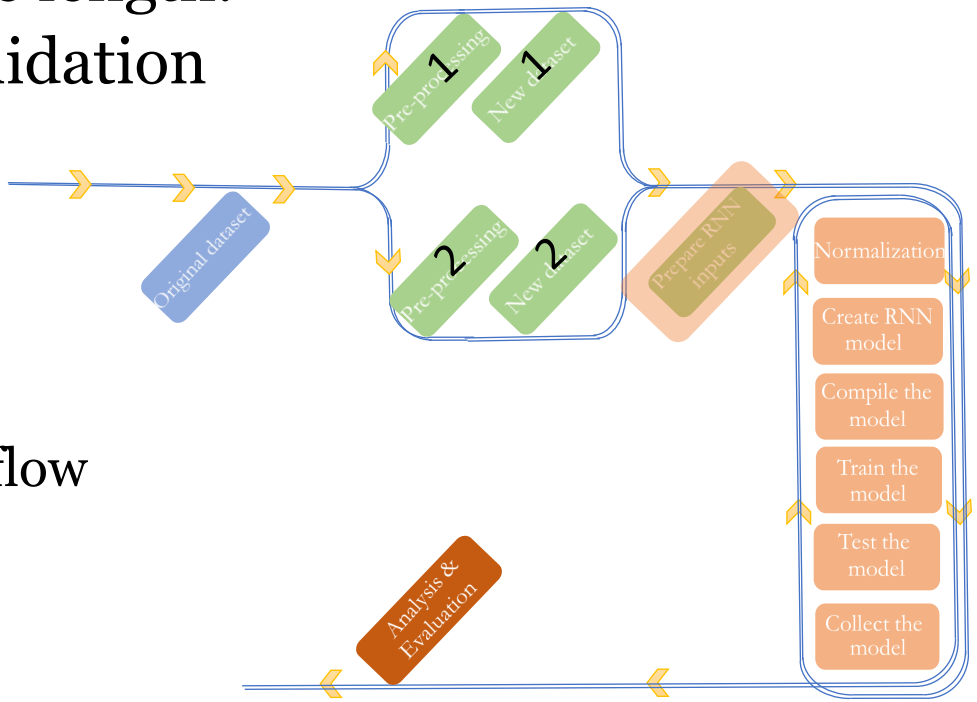
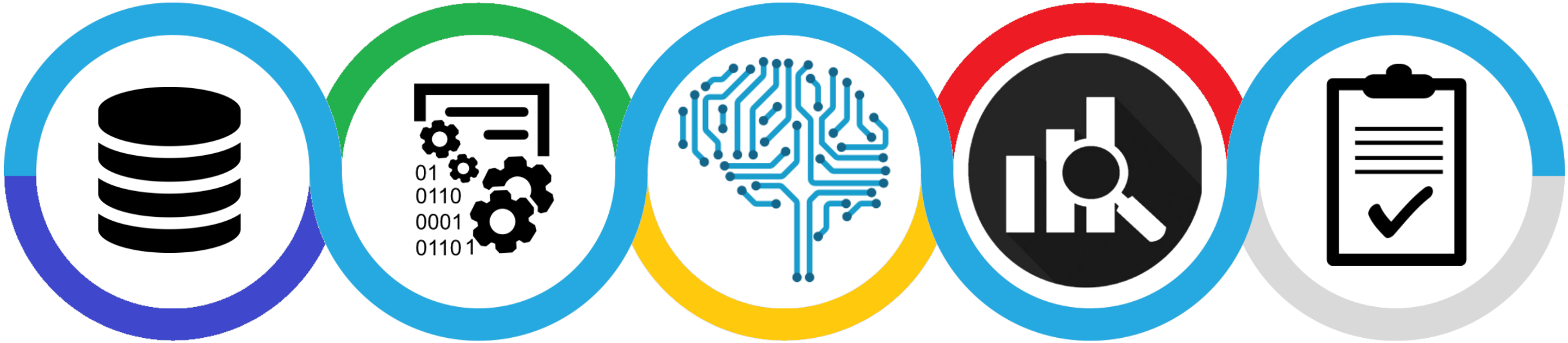


Fig 15 RNN-based experiments' workflow focused on data preparation part

Implementation Work Flow



Original dataset | Data processing | Classification step | Evaluation step | Results

Classification step
Recurrent Neural Networks (Long short-term memory)

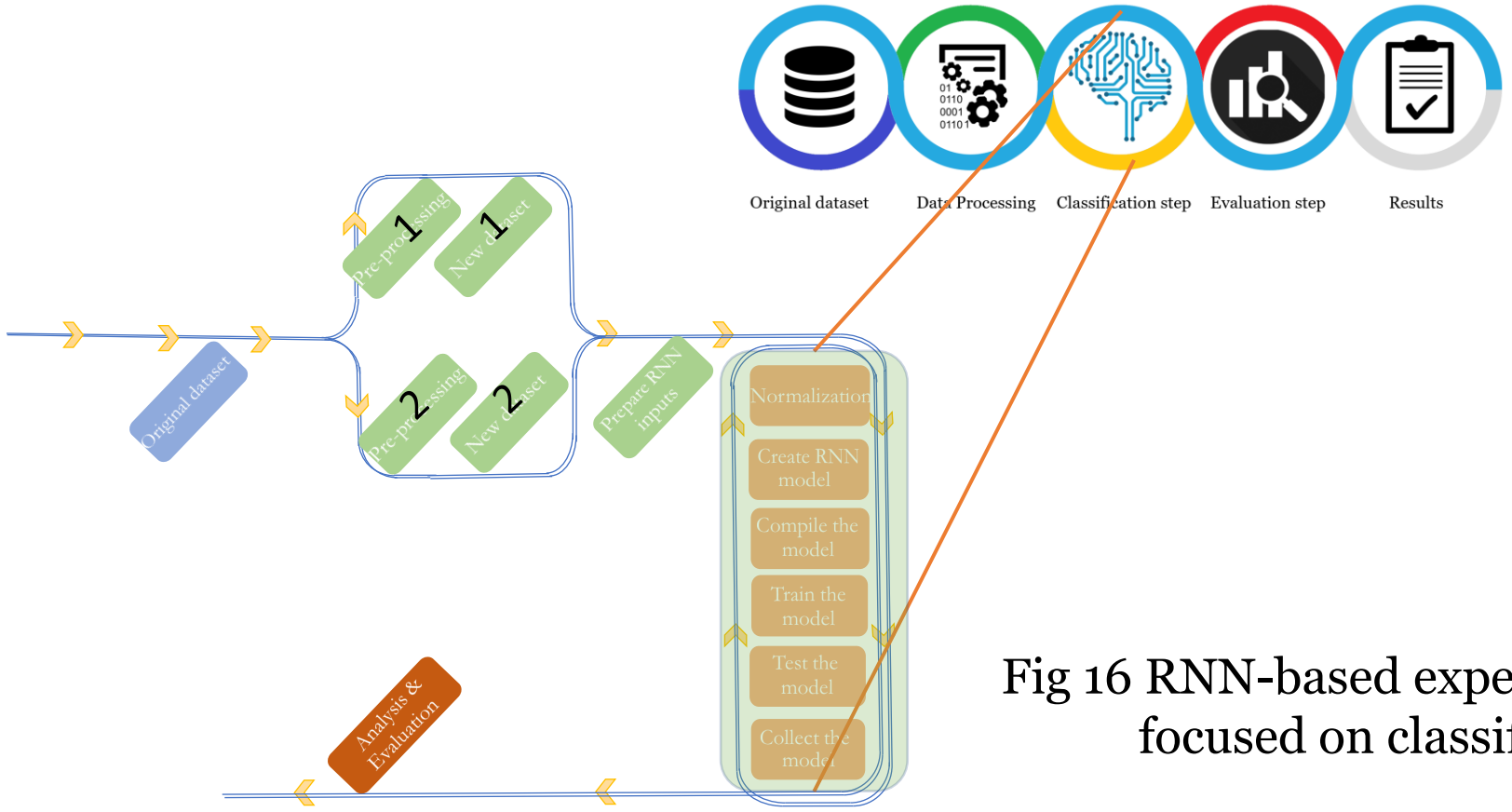


Fig 16 RNN-based experiments' workflow focused on classification part

Classification step

Recurrent Neural Networks (Long short-term memory)

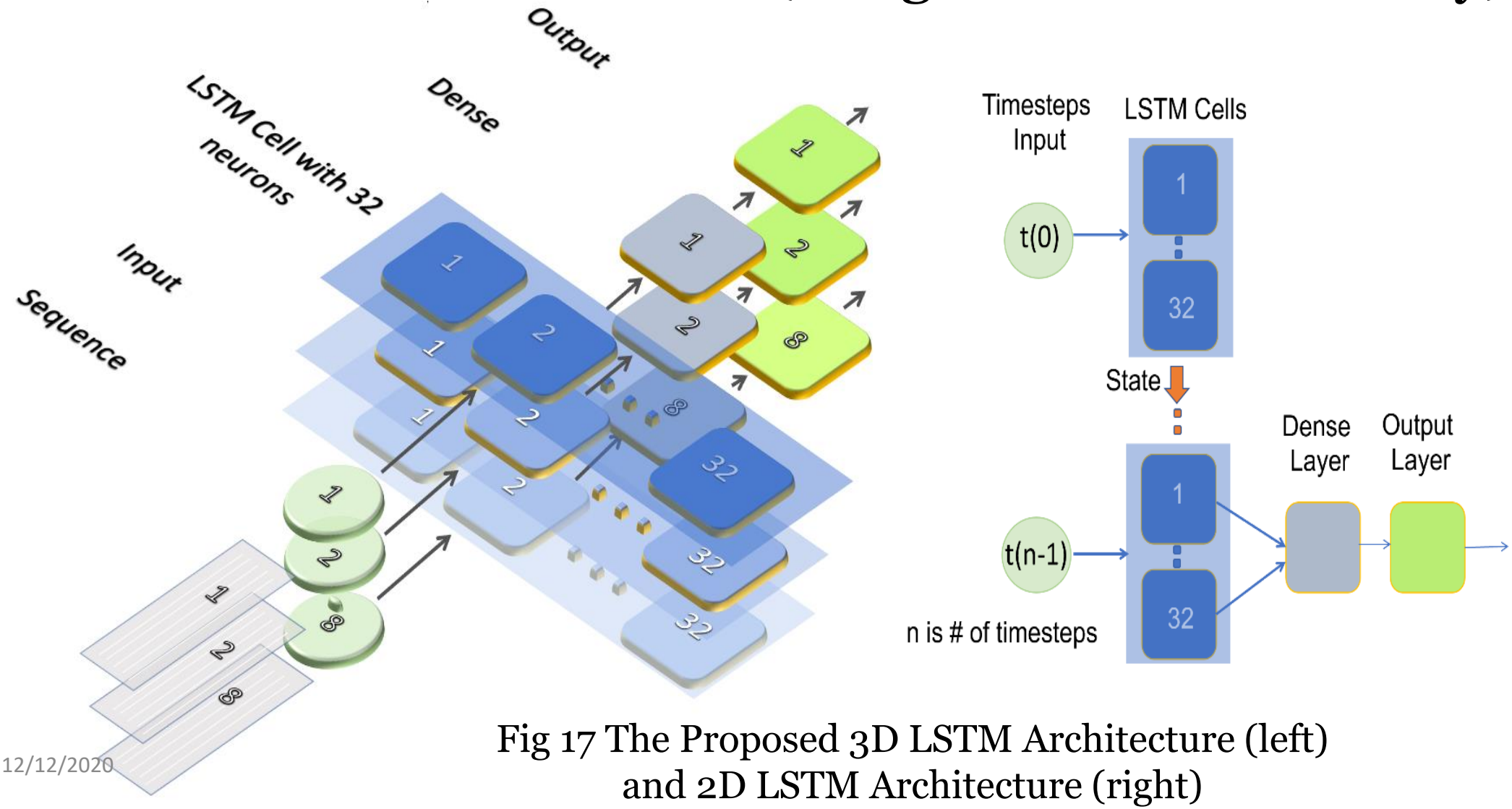
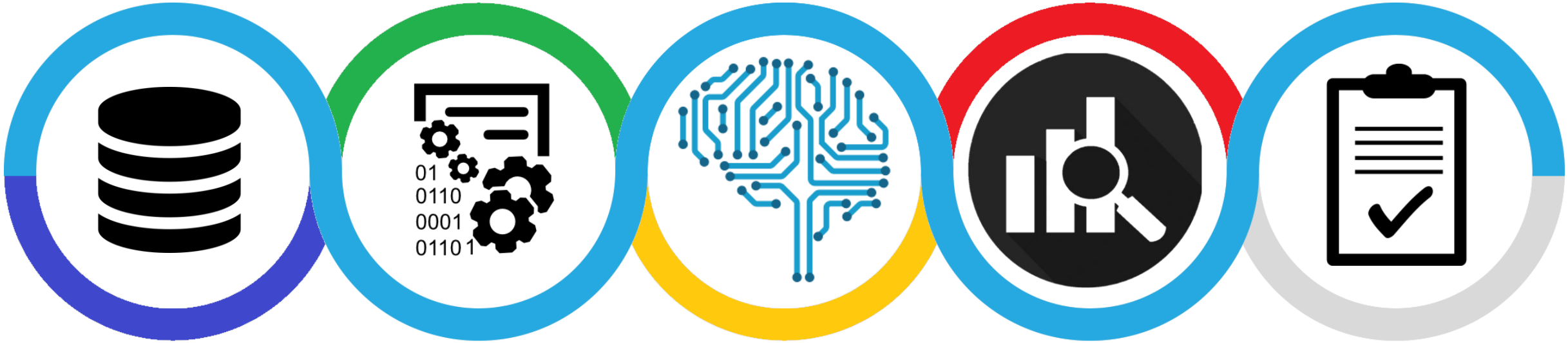


Fig 17 The Proposed 3D LSTM Architecture (left) and 2D LSTM Architecture (right)

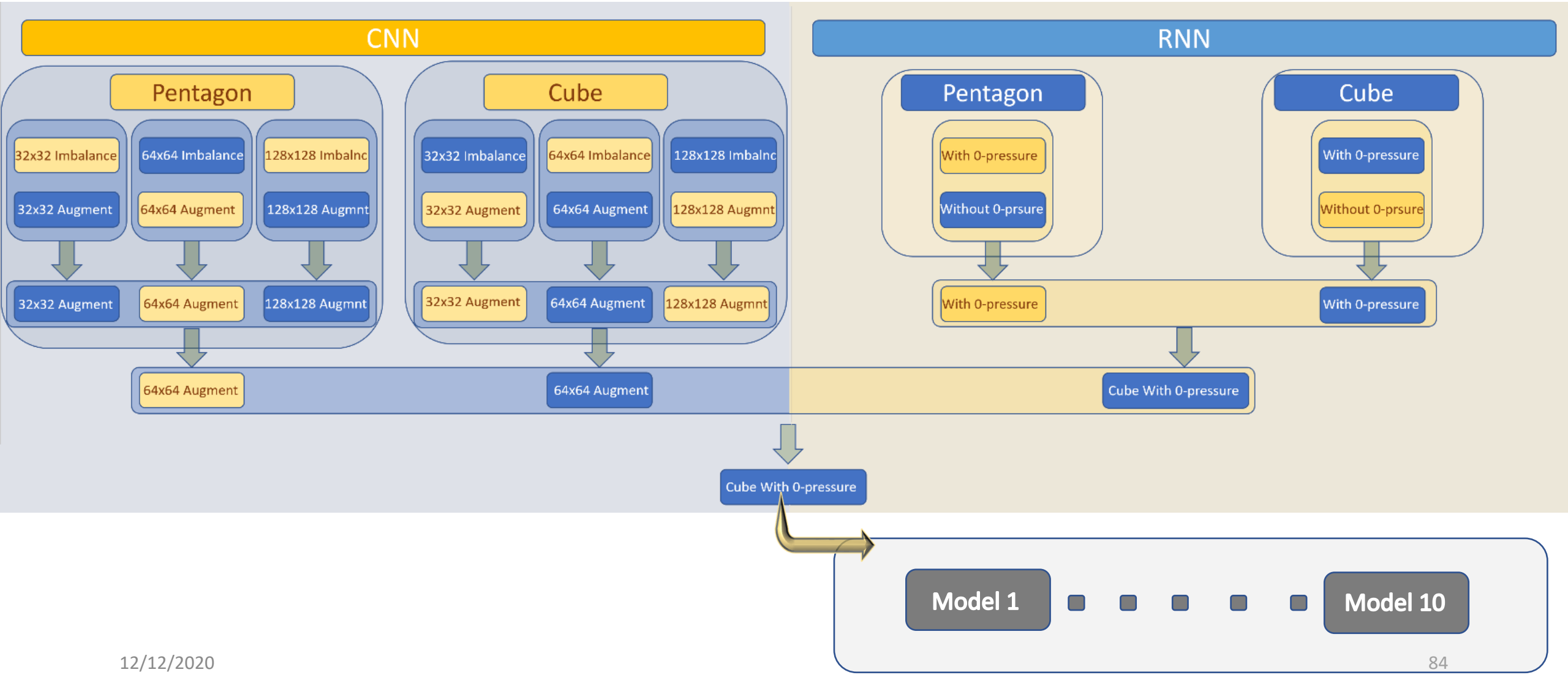
Implementation Work Flow



Original dataset | Data processing | Classification step | Evaluation step | Results

Evaluation plan

Fig 18 All experiments comparisons



Evaluation plan

- Phase 1: Evaluating the Experiments
  - ✓Mann-Whitney U Test two-tailed
  - ✓Kruskal-Wallis Test
  - ✓Post hoc test
    (Tukey test
    honestly significant
    difference (HSD))

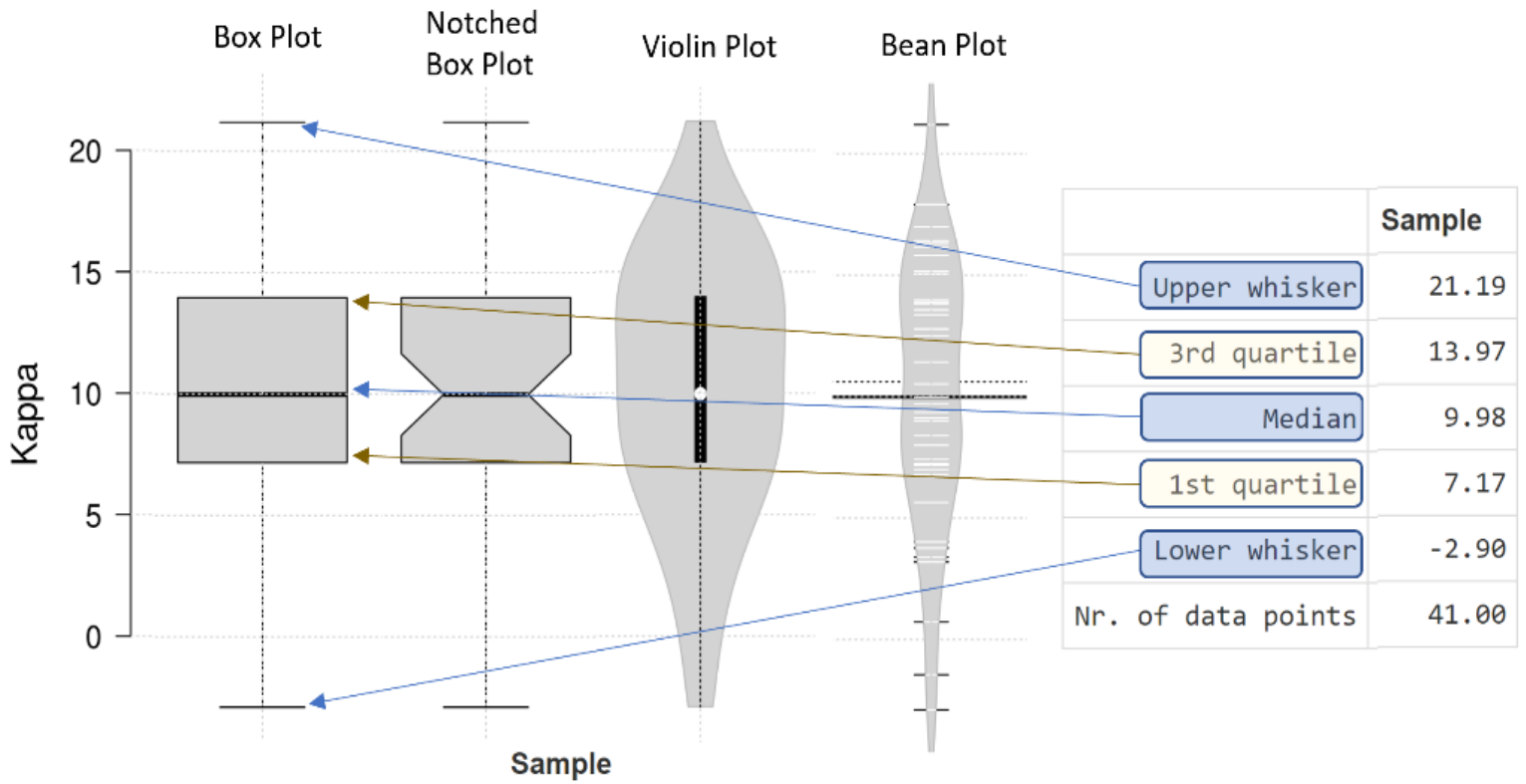


Fig 19 Box plot, notched box plot, violin, bean plots and statistical summary example

Evaluation

- Phase 2: Evaluating the Models

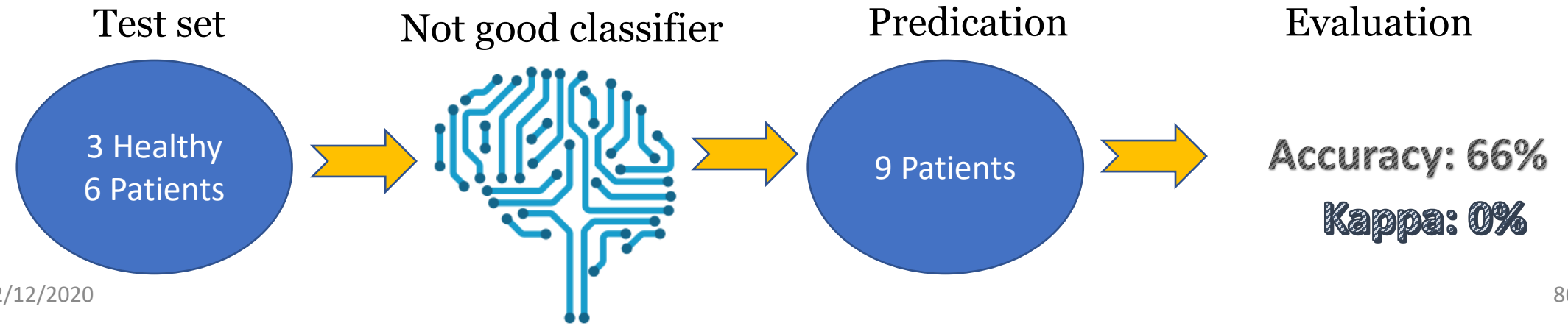
✓ Confusion matrix ✓ Specificity ✓ Sensitivity (Recall) ✓ Precision

✓ Classification accuracy ✓ Kappa ✓ Training time ✓ Average precision score

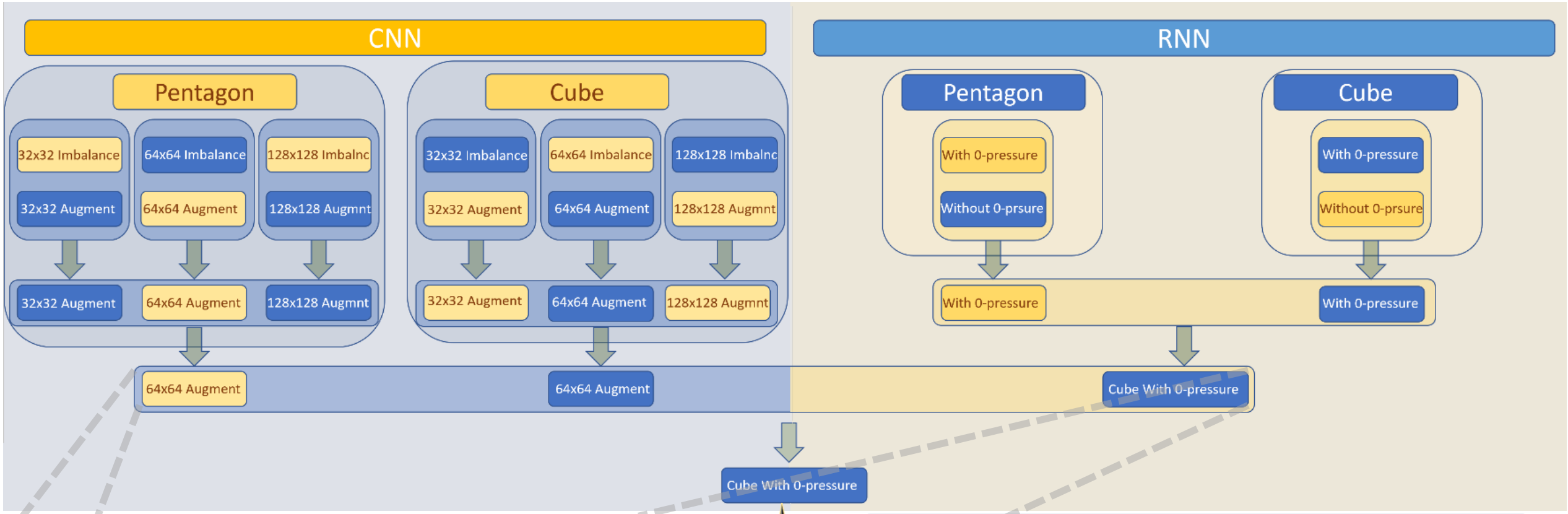
✓ Training accuracy & error VS epoch ✓ Validation accuracy & error VS epoch

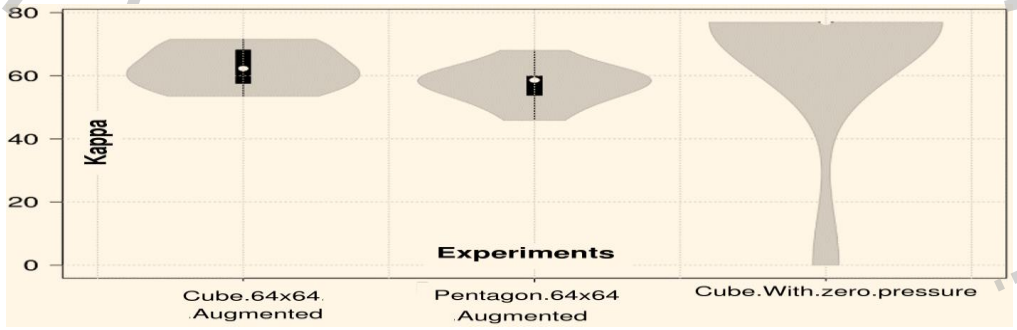
✓ Precision-Recall curve

- Kappa Vs Classification accuracy example



Evaluation





	precision	recall	f1-score	support
0 (Control)	0.75	1.00	0.86	3
1(Patient)	1.00	0.83	0.91	6
avg / total	0.92	0.89	0.89	9

Kappa: 76.92%
Specificity: 100%
Accuracy: 88.89%
Avg-Precision:98%
2.34 Hr

Discuss the best approach

Kappa: 76.92%

Accuracy: 88.89%

Recurrent Neural Networks Time-series dataset With zero-presure Cube

Discuss the best approach

Kappa: 76.92%

Accuracy: 88.89%

Recurrent Neural Networks Time-series dataset With zero-presure Cube

Time-series datasets include many useful features, and normally more good information leads to higher chance to classify patients and control individuals

timestamp	x coordinate	y coordinate	pen angle in x plane	pen angle in y plane	pressure
0	0.60061515525	0.5797397931	0.675101995	-0.495138138	0.052785925
8	0.6006889060	0.5797397931	0.675101995	-0.495138138	0.075268819
9	0.6007874100	0.5797397931	0.669257223	-0.505829691	0.092864125

Discuss the best approach

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Recurrent Neural Networks Time-series dataset | With zero-presure | Cube

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Perhaps this is because the subjects spend a long time holding the pen before or after the drawings task which increases the chance to obtain more useful information.

Discuss the best approach

Kappa: 76.92%

Accuracy: 88.89%

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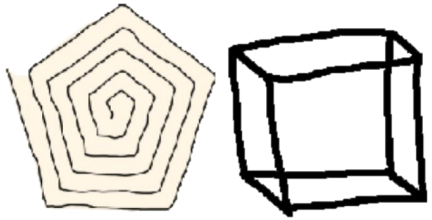
Drawing a 3D shape (cube) is harder than drawing a 2D shape (pentagon)



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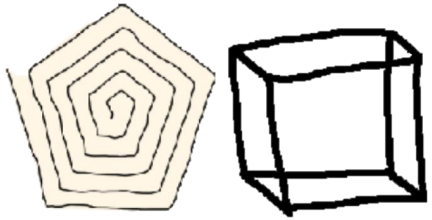
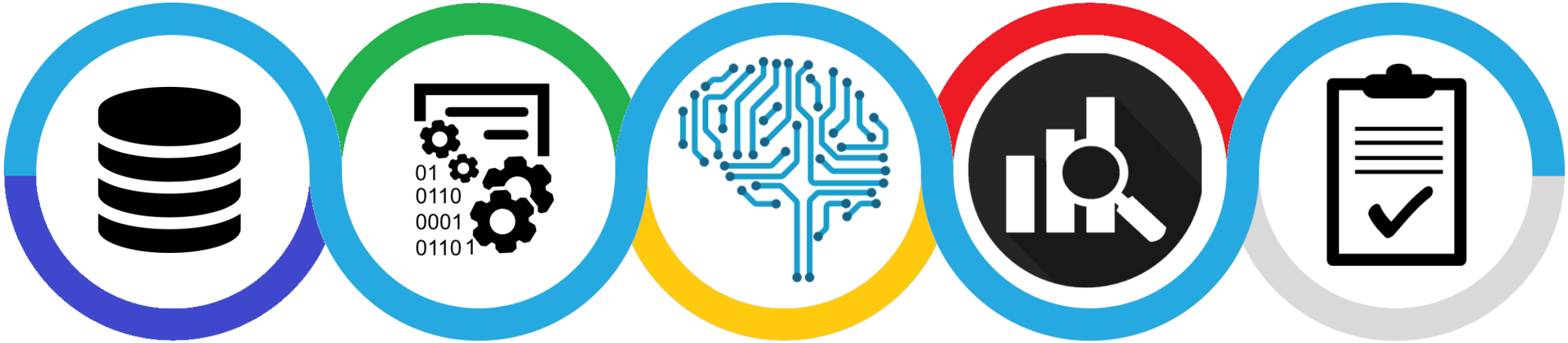


But this approach takes  **24.5 Hr** **training time**

Implementation Work Flow



Original dataset

Data processing

Classification step

Evaluation step

Results

Results

- **Effect of image size**

64x64 pixels is the most suitable size to contain the image data under our CNN configurations.

- **Effect of deep learning technique and dataset type**

The harder disease exam is more discriminative and effective to distinguish healthy subjects from individuals with PD.

- **Effect of augmentation**

Datasets with augmentation (i.e. balanced datasets) in all cases lead to better results than the imbalanced datasets.

- **Effect of removing zero pressure**

Keeping the zero pressure information is meaningful in terms of the differentiation between patients and control subjects.

Future work

- Investigate classifying disease stages.
- Extract knowledge from the trained models.
- We plan to publish a journal paper.

Tips for your future projects

Potential problem	Potential solution
New techniques for your project	RNN and CNN
Time series samples have variety of lengths	Zero-padding
Small imaging dataset	Augmentation
Imbalance imaging dataset	Augmentation
Speed up the learning process	Normalisation
Compare many experiments' results	statistical tests
Use kappa instead of classification accuracy	

Thank you

Any Question?..