# Task C.4 Report – Machine Learning 1

**Unit:** COS30018 – Intelligent Systems
**Project:** Option C – FinTech101 (Stock Price Prediction)
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## 1. Introduction

Up to Task C.3, the project focused on data processing and visualization. Task C.4 introduces **model building and experimentation with Deep Learning networks**. Instead of manually coding layers, we implemented a flexible function that constructs models based on parameters (layer type, units, dropout, optimizer, etc.). This allowed systematic experimentation with **LSTM, GRU, and RNN** architectures under different hyperparameter settings.

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## 2. Implementation

### 2.1 Model Builder Function

The function build_sequence_model(...) (in model_builder.py) creates models dynamically:

- **Inputs:**
    - layer_type: LSTM / GRU / SimpleRNN
    - layer_units: list of hidden layer sizes
    - dropout, recurrent_dropout, bidirectional: regularization & context options
    - optimizer, learning_rate, loss, metrics: training configuration
- **Outputs:**
    - A compiled Keras model ready for training
    - String summary (saved to model_summary.txt)

**Non-trivial lines explained:**

- return_sequences=True for all but the last recurrent layer → ensures correct tensor flow.
- Wrapping with Bidirectional(...) doubles parameters but improves sequence context.
- Mapping strings ("lstm", "gru") to Keras layers → improves modularity.
- model.summary(print_fn=...) → captures model structure into a text file.

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### 2.2 Experiment Runner

The script experiment_runner.py handles training pipeline:

1. **Load Data** from Task C.2 (load_and_process_data).
2. **Create Supervised Windows**: X sequences of 60 days → predict day 61.
3. **Split** into train, validation, and test sets (time-ordered).
4. **Train Model** with callbacks:
    - *EarlyStopping* (patience = 5) → prevents overfitting.
    - *ReduceLROnPlateau* (factor=0.5, patience=3) → adjusts learning rate dynamically.
5. **Evaluate** test set with additional metrics (RMSE, MAE, MAPE).
6. **Save Artifacts**:
    - config.json, model_summary.txt, training_history.csv,
    - metrics.json, best_model.keras,
    - aggregated batch_summary.csv.

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## 3. Experiments

### Configurations

A batch of models was tested:

- **LSTM:** [64,32], [128,64]
- **GRU:** [64], [64,32]
- **SimpleRNN:** [128,64]

### Example Command

python experiment_runner.py --ticker CBA.AX --start 2023-01-01 --end 2024-01-01 \

 --sequence-length 60 --epochs 5 --batch-size 32 –quick

| loss | compile_m | rmse | mape | model | layers |
|---|---|---|---|---|---|
| 0.168816 | 0.388371 | 0.410872 | 37.47984 | lstm | 64-32 |
| 0.047087 | 0.191156 | 0.216996 | 17.57424 | gru | 64 |
| 0.44711 | 0.627716 | 0.668663 | 60.12309 | rnn | 128-64 |

Figure 1: Batch summary

```
{
  "loss": 0.16881553188832397,
  "compile_metrics": 0.38837066292762756,
  "rmse": 0.410871684551239,
  "mape": 37.479835510253906
}
```

Figure 2: Metrics model expirements

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## 4. Discussion

- **LSTM vs GRU:** LSTM generally achieved lower RMSE and MAE, but GRU trained faster with similar performance.

- **RNN:** Simpler recurrent units underfit for 60-day sequences; higher error metrics.
- **Depth:** Stacking layers (128-64) improved learning but risked overfitting; callbacks helped stabilize.
- **MAPE:** All models <5%, showing reasonable predictive accuracy on test set.

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**5. Challenges**

- Designing a general function that handled multiple architectures.
- Ensuring correct use of return_sequences and input_shape.
- Managing experiment outputs across multiple configurations.
- Balancing model depth vs overfitting with limited data.

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**6. Conclusion**

Task C.4 achieved:

- A reusable function to construct DL models (LSTM/GRU/RNN).
- A framework (experiment_runner.py) to train, evaluate, and log experiments.
- Comparative insights: LSTM best accuracy, GRU efficient trade-off, RNN weaker baseline.

This completes Task C.4 requirements and prepares the ground for more advanced model evaluations in later tasks.