1.

A. I chose “median_income” and “total_rooms” for my small NN.

B. Did not get around to doing this.

C.

```
{'Small Model RMSE': 96259.3133685046, 'Full Model RMSE': 72886.54157952222}
```

The small model is more practical, even though it's less accurate. The accuracy is only about 25% worse. But it’s far more practical to interpret and run on a large scale. I think it depends on your use case. If we want accuracy, use the large model 100/100 times.

#2.

A.

```
Epoch 37/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 33ms/step - accuracy: 0.9915 - loss: 0.0275 - val_accuracy: 0.8800 - val_loss: 1.0087
Epoch 38/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 34ms/step - accuracy: 0.9919 - loss: 0.0330 - val_accuracy: 0.8300 - val_loss: 0.8853
Epoch 39/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 33ms/step - accuracy: 0.9988 - loss: 0.0142 - val_accuracy: 0.8500 - val_loss: 0.6630
Epoch 40/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 34ms/step - accuracy: 0.9811 - loss: 0.0400 - val_accuracy: 0.8800 - val_loss: 0.5783
Epoch 41/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 33ms/step - accuracy: 0.9921 - loss: 0.0282 - val_accuracy: 0.8800 - val_loss: 0.6132
Epoch 42/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 33ms/step - accuracy: 0.9887 - loss: 0.0210 - val_accuracy: 0.8600 - val_loss: 0.5449
Epoch 43/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 34ms/step - accuracy: 0.9964 - loss: 0.0159 - val_accuracy: 0.8700 - val_loss: 0.8192
Epoch 44/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 33ms/step - accuracy: 0.9855 - loss: 0.0158 - val_accuracy: 0.8700 - val_loss: 0.7827
Epoch 45/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 34ms/step - accuracy: 0.9942 - loss: 0.0103 - val_accuracy: 0.8600 - val_loss: 0.8189
Epoch 46/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 33ms/step - accuracy: 0.9994 - loss: 0.0079 - val_accuracy: 0.8600 - val_loss: 0.7995
Epoch 47/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 33ms/step - accuracy: 1.0000 - loss: 0.0189 - val_accuracy: 0.8600 - val_loss: 1.2930
Epoch 48/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 34ms/step - accuracy: 0.9914 - loss: 0.0166 - val_accuracy: 0.8400 - val_loss: 1.9474
Epoch 49/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 33ms/step - accuracy: 0.9709 - loss: 0.0347 - val_accuracy: 0.8600 - val_loss: 0.7143
Epoch 50/50
10/10 ━━━━━━━━━━━━━━━━━━━━ 1s 32ms/step - accuracy: 1.0000 - loss: 0.0128 - val_accuracy: 0.8600 - val_loss: 1.2972
```

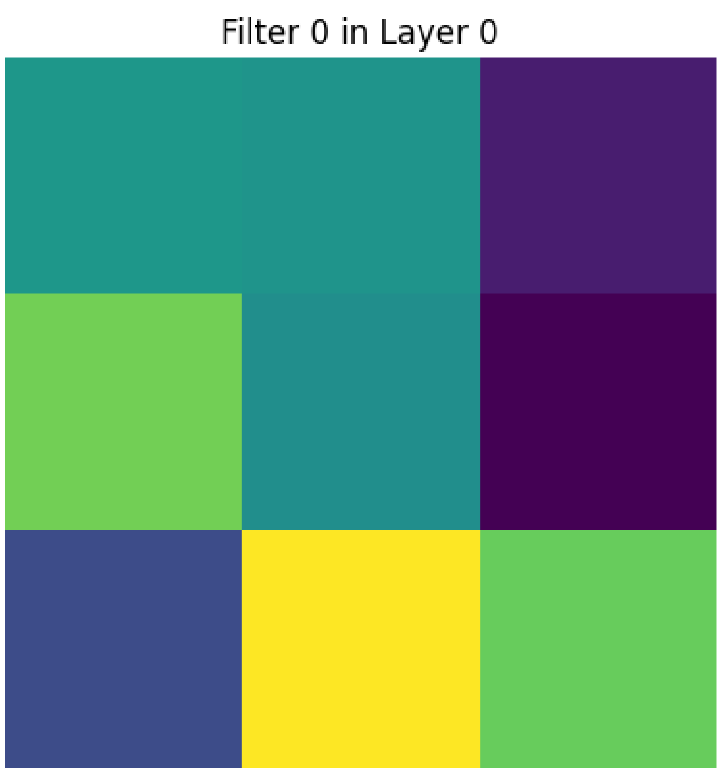
Pretty good accuracy. I did have a model get around 90% on validation accuracy, but I accidentally lost that and could never get similar results.

B. I did not get around to examining the outputs. It was interesting to do this in class, though. I examined the layer outputs as they got more interpretable to see whether the layer looked at curved lines, straight lines, vertical/horizontal lines, etc.

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 60, 50)	10,400
dropout (Dropout)	(None, 60, 50)	0
lstm_1 (LSTM)	(None, 60, 50)	20,200
dropout_1 (Dropout)	(None, 60, 50)	0
lstm_2 (LSTM)	(None, 50)	20,200
dropout_2 (Dropout)	(None, 50)	0
dense (Dense)	(None, 15)	765

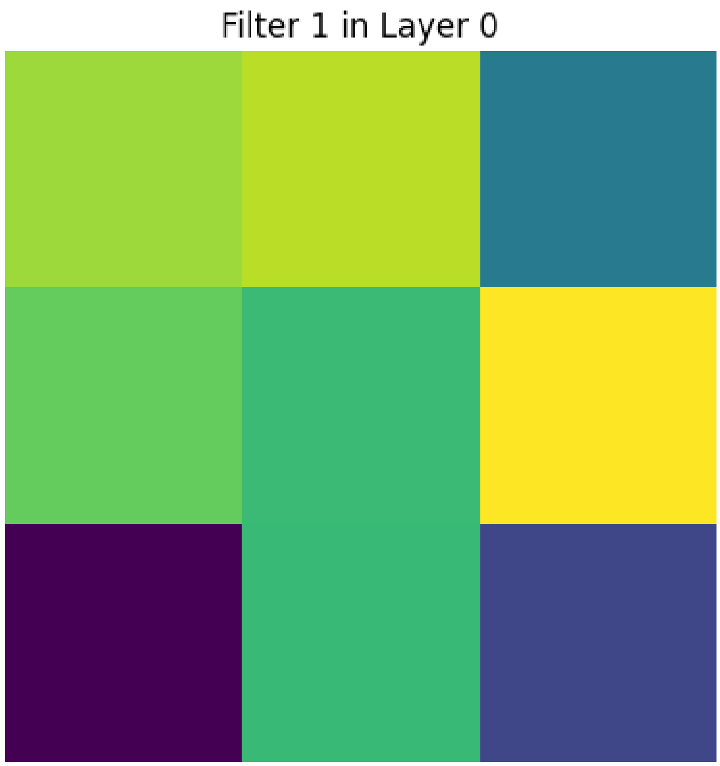
Total params: 51,565 (201.43 KB)
Trainable params: 51,565 (201.43 KB)
Non-trainable params: 0 (0.00 B)

C. Filter examination.



This filter visualization only looks at the first channel, although we have 3 channels (R,G,B).

Not much insight can be derived; it is a 3x3 filter, though. This is at the first layer (layer 0), so we are still looking at very complex data. It has not been simplified.



This also looks at first channel in R,G,B. Some insights can be derived by the computer, but as humans we cannot really get much out of the image. We do see some pixels are the same or similar in color though.

D. Wrong Predictions

True: 0, Predicted: [1]

This picture must have just needed to be bigger to capture enough edges, and I wonder why the algorithm got it wrong. He looks identifiable, but I'm unsure what my Model was thinking.

This second wrong prediction is from the same photographer at the same event. Maybe it was a clone, and my model discovered it was not the real Leo.

3.

B.

```
Near Future (Days 1-7): MAE = 8.17, RMSE = 10.28
Far Future (Days 8-15): MAE = 10.96, RMSE = 13.72
The model is more accurate in the near future (Days 1-7).
```

C. Invest 100$ daily for 15 days, if stock is predicted to go up.

```
# Example strategy: Invest $100 when predicted stock goes up

initial_investment = 100
gains = []
for i in range(len(predictions)):
    if predictions[i, -1] > predictions[i, -2]:  # Predicted increase
        gains.append(initial_investment * (y_test_rescaled[i, -1] /
y_test_rescaled[i, -2]))
```

```
    else:
        gains.append(initial_investment)

final_balance = sum(gains)
print(f"Final Investment Balance: ${final_balance:.2f}")
```

```
Final Investment Balance: $23706.18
```

#4. Article Review On the ethics of algorithmic decision-making in healthcare

The authors argue that while machine learning can enhance the accuracy of medical diagnoses and treatment recommendations, it introduces trade-offs in epistemic and normative domains.

A.

Epistemic Trade-offs: Machine learning algorithms can process complex data quickly and reduce human cognitive biases. However, their opacity and overconfidence undermine the clinician's epistemic authority, especially in cases of disagreement between the algorithm and the clinician.

Ethical Pitfalls: Machine learning challenges accountability. When algorithms fail, it's unclear who bears responsibility—clinicians, healthcare institutions, or developers. Algorithms may foster defensive medical practices, leading to overreliance on algorithmic outputs and reduced patient autonomy. Biases in algorithms can exacerbate disparities, particularly for underrepresented populations.

Structural Impacts: Algorithm deployment reshapes evidentiary norms and the conceptualization of health and disease, potentially privileging the values embedded in training data over localized or individual clinical judgments.

Call for Ethical Reflection: The authors stress the importance of transparency and fairness in algorithmic deployment and advocate for ongoing ethical scrutiny to ensure machine learning enhances rather than hinders medical practice.

B.

I generally agree with the authors' concerns and arguments, particularly their emphasis on transparency, fairness, and the need for ethical reflection in using machine learning in healthcare. However, evaluating their predictions over time reveals accurate foresight and evolving challenges.

Accuracy of Predictions: Concerns about algorithmic opacity and its impact on epistemic authority remain relevant in 2024. The paper was published in late 2019. Despite advancements in explainable AI, achieving full transparency is still a challenge. Biases in training data leading to inequities in algorithmic performance have been increasingly documented, reinforcing the authors' warnings.

Impact of Algorithmic Integration: The notion of defensive medicine has materialized, with clinicians sometimes overly reliant on algorithmic suggestions to mitigate liability risks. Ethical debates around accountability have intensified, as seen in legal and policy discussions surrounding AI failures.

Evolving Landscape: While the authors recognized the potential for machine learning to shift healthcare norms, the pace of adoption has varied. Regulatory hurdles and a lack of prospective studies have slowed implementation in some areas. Efforts to address fairness through diverse datasets and inclusive algorithm design are more prominent now, but challenges remain.