DenseNet Feature Embeddings for Thoracic Disease Diagnosis

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Introduction

Chest X-ray scans are the most frequent type of radiology exam worldwide, and are commonly used to diagnose pneumonia, lung cancer, and dozens of other thoracic illnesses. However, proper diagnosis is challenging, as a single scan can reveal multiple illnesses, and radiologists often disagree in their diagnoses. In recent years, deep convolutional neural networks have been shown to approach or even exceed human doctors at this diagnosis task. In this work, we build on the DenseNet-based models developed in several recent papers [CITATIONS]. To understand the behavior of these models, we investigate feature embedding vectors output by DenseNet and find that they exhibit clustering properties. By leveraging these embeddings with different final classifiers, we produce new state-of-the-art results for thorax disease classification.

Dataset

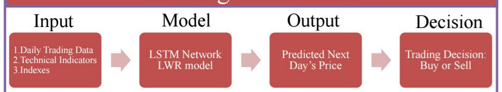
Time series data of stock price of Intel:

Data resource:
https://www.kaggle.com/nih-chest-xrays/data

Data classes:
14

Data set size:
- Train set: 2 years( )
- Dev set: 3 months( )
- Test set: 3 months( )

Trading Framework



Data Preprocessing and Features

The input features we choose consist of three sets of variables. The first set is historical daily trading data of INTC including previous 5 day's adjusted closing price and log returns, Open/Close price, High/Low price, and trading volume. These variables provide basic information about INTC. The second set is the technical indicators that demonstrate various characteristics of the stock behavior. The third set is index: S&P 500 (^GSPC), CBOE Volatility Index (VIX), and PHLX Semiconductor Sector (^SOX).

- **Daily Trading Data of INTC**
  - Previous 5 days' prices and log returns
  - Open/Close price, High/Low price, and Trading volume

- **Technical Indicators of INTC(computed based on the trading data)[3]**
  - Rolling Average/Standard Deviation with 5 and 10 days window
  - Bollinger Band: two standard deviations from a moving average
  - Average True Range: a measure to volatility of price
  - 1 month Momentum: the difference between current price and the price 1 month ago
  - Commodity Channel Index: an identification of cyclical trends
  - Rate of Change: the momentum divided by the price 3 months ago
  - Moving Average Convergence Divergence: a display trend following characteristics and momentum characteristics
  - Williams Percent Range: a measure of the buying and selling pressure

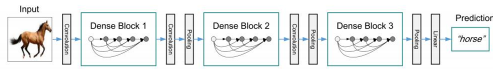
- **Index of the Market and Sector**
  - S&P 500, VIX, and PHLX Semiconductor Sector

***All of the variables are scaled between 0 and 1 before we feed them into the model.**

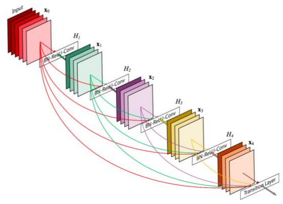
Models

- **DenseNet Architecture**

Block Structure:



Dense Block:

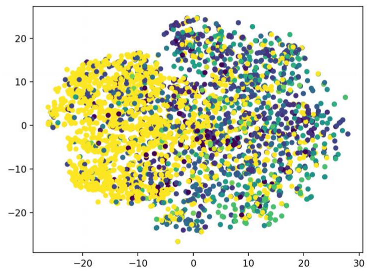


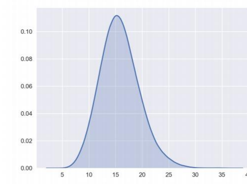
Parameters For DenseNet:
- Optimizer: *Adam*
- Library: *PyTorch*
- Hidden layers #: 169
- Delay #: 10
- Training Step #: 5000

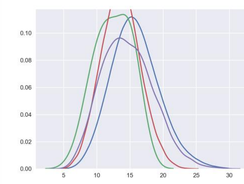
Experiments

Period	CheXNet	DenseNet169	One-vs-Rest Random Forest	k-Nearest Neighbors	Ensemble
Atelectasis	0.8094	0.8280	0.8199	0.7252	0.8284
Cardiomegaly	0.9248	0.9147	0.8909	0.6945	0.9116
Effusion	0.8638	0.8888	0.8814	0.8047	0.8889
Infiltration	0.7345	0.7201	0.7069	0.6598	0.7216
Mass	0.8676	0.8524	0.8621	0.6366	0.8509
Nodule	0.7802	0.7849	0.7693	0.5978	0.7860
Pneumonia	0.7680	0.7644	0.7502	0.6062	0.7686
Pneumothorax	0.8887	0.8816	0.8959	0.7594	0.8775
Consolidation	0.7901	0.8092	0.8097	0.6997	0.8101
Edema	0.8878	0.8941	0.9030	0.7805	0.8912
Emphysema	0.9371	0.9222	0.8735	0.7125	0.9307
Fibrosis	0.8047	0.8397	0.7824	0.6391	0.8393
Pleural Thickening	0.8062	0.7918	0.8104	0.6752	0.7911
Hernia	0.9164	0.8903	0.7974	0.6122	0.8712

Embedding Analysis







Conclusion

- Deeper DenseNets, along with careful tuning, can improve the accuracy of diagnosis on chest x-rays.
- The performance of LSTM is more robust than LWR. LSTM has smaller MSE than LWR for both Dev Set and Test Set, and it has less deviation in the prediction price plot.
- The strategy based on LSTM yields higher returns and Sharpe Ratio than LWR-based strategy and simple Buy and Hold Strategy.
- However, the prediction by these models become inaccurate when the price changes dramatically.

Outlook

- Tuning hyper parameters and adding regularization term would improve the performance of LSTM.
- Trading strategy with reinforcement learning could generate more stable and higher returns.

References

[1] Andres et al.: High-Frequency Trading Strategy Based on Deep Neural Networks(2016)
[2] Hands-On Machine Learning with Scikit-Learn and TensorFlow
[3] A deep learning framework for financial time series using stacked autoencoders and long short term memory
[4]Understanding LSTM Networks, Colah's blog,
http://colah.github.io/posts/2015-08-Understanding-LSTMs/