Reclassification of CME Market Sentiment Meter State using image recognition technique

By

Zijun Wu,

Qiansheng Zhou,

Xinglin Chen,

Azizha Zeinita,

Supervisor: Abid Ali

A Capstone Project

Submitted to the University of Chicago in partial fulfilment

of the requirements for the degree of

Master of Science in Analytics

Division of Physical Sciences

Nov 2022

Abstract

In the real time market, our client CME group would like to predict future trend with current trend to maximize the profits in the industry like gold, treasuries, corn and equites. They currently have a market sentiment meter which classify the distributions to 4 parts: complacent, balanced, anxious and conflicted. This research will create an image recognition model to improve the accuracy of reclassification sentiment states when significant reasons that lead market changes. CNN will be main algorithm this project use to solve this problem.

Keywords: Image recognition, machine learning, CNN, financial market, trading, classification

Executive Summary

CME group is one of the biggest trading platforms in the world. The company's CME, CBOT, NYMEX and COMEX, offer the broadest range of global benchmark products across all major asset classes, including futures and options based on interest rates, equity indices, foreign exchange, energy, agricultural commodities, metals, weather and real estate. Partnering with 1QBit, CME Group created the Market Sentiment Meter to help assess the magnitude of historical market sentiment. MSM currently has four different states: complacent, balanced, anxious and conflicted. However, the mixture model cannot accurately reclassify sentiment states when sentiment of financial products changes from one state to another (especially Conflicted). As a result, the project needs to create an image recognition model to improve the accuracy of reclassification sentiment states.

The team reviewed couple of papers before research and choose 3 papers as main reference which are Pathological Myopia Image Recognition Strategy Based on Data Augmentation and Model Fusion, ImageNet Classification with Deep Convolutional Neural Networks and Is Deep Learning for Image Recognition Applicable to Stock Market Prediction? In the paper, there are couple of methods mentioned related to solve this problem. The team decide to consider and try CNN and LSTM as our main algorithm to solve the problem. The team will compare the goodness of fit matrix such as accuracy score, MAE, RMSE, and R square and confusion matrix to see what the expected accuracy and loss of both image recognition model and the MSM model are.

Table of Contents

List of Figures

List of Tables

Introduction

CME Group

With a 150-year history, the Chicago Mercantile Exchange (CME) was the first place where market participants could go to buy and sell commodities to manage risk. CME Group provides a marketplace for buyers and sellers, connecting individuals, businesses or institutions that need to manage risk or are willing to profit from risk-taking.

The company's CME, CBOT, NYMEX and COMEX, offer the broadest range of global benchmark products across all major asset classes, including futures and options based on interest rates, equity indices, foreign exchange, energy, agricultural commodities, metals, weather and real estate.

Through the CME Globex electronic trading platform, users worldwide are able to access this financial derivatives market. In addition, Chicagoland operates CME Clearing, the world's leading central counterparty clearing house. The team are the counterparty to every transaction that occurs in the markets, so the integrity of the markets is protected, and third-party credit risk is largely eliminated.

Market Sentiment Meter

Partnering with 1QBit, CME Group created the Market Sentiment Meter to help assess the magnitude of historical market sentiment. Using eight of CME Group's major futures and options products, the tool tracks sentiment changes. Based on data back to 2012, the Market Sentiment

Meter updates daily with a variety of metrics available through CME DataMine, a cloud-based historical data platform.

MSM currently has four different states: COMPLACENT when there is low level of market anxiety, BALANCED when there is normal level of market anxiety, ANXIOUS when there is high level of market anxiety and CONFLICTED when there is price gap anxiety.

Problem Statement

Context

CME group uses a parametric mixture model CME Market Sentiment Meter (MSM) to classify market sentiment into four states: balanced, complacent, anxious, and conflicted. The mixture model is comprised of a traditional distribution model and the other enhanced by three vital factors that affect risk profile, intraday high-low price spread, put/call options volume ratio and the relationship between historical volatility and implied volatility.

Continuedly using MSM model will miss the sign of sentiment transition and stays in the original classification, which is no longer the correct case. CME will lose the signal from the market and not be able to make good judgements on financial products as well as investment decisions.

However, the mixture model cannot accurately reclassify sentiment states when sentiment of financial products changes from one state to another (especially Conflicted). As a result, this project will create an image recognition model to improve the accuracy of reclassification sentiment states.

Significance of the problem

Image recognition model can act as a sentiment change indicator. It can bring assistance and improvement for MSM model. By developing the image recognition model, the algorithm can minimize conflict cases in model prediction when sentiment changes from one state to another. For example, the algorithm can classify sentiment state as 'Anxious' instead of 'Balanced' if the distribution is skewed and data matches certain criteria.

Desired solution and benefits

If the model is improved, CME company will have a more accurate reclassification model. Because the image recognition models provide identifying patterns more effectively, it could possibly reduce the future time, effort and costs in identifying different market sentiments. The model can possibly get rid of unnecessary data and decrease the data storage pressure on the system. At the same time, CME group will be more informative on different states of market sentiment and will be able to identify potential risks and returns for financial products. As a result, CME company can adjust both short-term and long-term investment strategies and update the investment portfolio.

Challenge

Although the MSM works as expected about 95 to 99% of the time. But when sentiments change from balance to conflict, the period of transition needs to be reclassified. And at this time, for the slightest change in the distribution can represent the existence of a huge potential risk. So, the model needs to differentiate the weights where the distribution images are different and expect the method to amplify these small differences.

At the same time, most of the existing models are based on the analysis of price changes, while identification of the combined distribution images is different from the previous model analysis, which requires a lot of improvement and data processing, including normalize and standardize data

Analysis Goals

Objectives

The analysis aims to make a model for reclassifying current market sentiment categories into new categories by identifying distribution graph output using image recognition methodology. This model expected to show more accurate reclassifications of sentiment group during changing of market sentiment from one category to another and minimize conflict cases in model prediction.

How to accomplish the project

Image recognition is used to analyse and detect many types of elements in image, which can enable the automation of a specific task. This methodology can perform classification, tagging, detection, and segmentation. Image recognition is based on the Deep Learning algorithm, subcategory of Machine Learning based on Artificial Neural Network.

To accomplish the project purpose, Convolutional neural network (CNN) is used as a class of Artificial Neural Network (ANN) that is most commonly applied for analysing visual imagery. This methodology well-suited to classifying, processing and making predictions on dataset which lags consist of unknown duration between important events. In this project, CNN is used for feature extraction and classify the distribution graph based on those features. This way, the model is expected to have better performance on classifying the graph into more accurate market sentiment categories.

In term of dataset, the model will use historical market sentiment dataset from eight of CME Group's major futures and options products to be visualized into distribution graphs before the model proceed it as inputs for image recognition using CNN. As result, the model will get different kind of pattern classifications based on how it uses this method.

Outcomes

The team expect the image recognition model to perform better than MSM model in the aspect of classifying sentiment state changes in financial products. For the optimal expectation, the image recognition model would be expected to have higher performance on all eight financial products. In the research, the results will focus on comparing the differences with the original MSM classification and comparing the accuracy. In this way, the model focuses on the potential of image recognition to have more accurate prediction and faster response on market sentiment reclassification so that managements can adjust the investment portfolio and earn more profits for the company.

By applying the analysis, new market sentiment categories other than current classification will be accomplished with more accurate prediction outcome compared to current four categories. The accuracy of model used will be assessed by comparing analysis result based on the prediction of distribution graph identification using new sentiment categories with the real standard deviation events occurring.

Scope

The MSM data comprises eight futures products (S&P E-mini, US 10-Year Treasuries, Gold, Euro-FX, WTI, Crude Oil, Natural Gas, Corn, and Soybeans). Data is daily from January 2012, with settlement prices, high-low prices for the day, options implied volatility, put and call options volumes, and futures volumes.

The research focuses on the analysis of 256-element discreet distribution images using mechanical learning image recognition tools to improve on existing classifications in order to predict and analyse future market sentiment and risk.

Background

The client has previously collaborated with 1Qbit and already created one version of the Market Sentiment Meter to help assess the magnitude of historical market sentiment. They now would like to reclassify the market distributions to better predict the market. Though current accuracy is around 95 ~ 99%, when sentiment changes from one state to another (especially Conflicted), the transition period needs to be re-classified. Therefore, the main goal here is to re-classify related distribution to the designed category and make some improvements.

Literature Review

According to Journal of Healthcare Engineering, automatic identification of various retinal illnesses using fundus images is critical for clinical decision-making. For this task, this article uses convolutional neural networks (CNNs) because of the high model effectiveness. However, the high expressive ability of CNNs may lead to overfitting. To avoid overfitting while enriching datasets, data augmentation (DA) strategies have been proposed. Traditional DA algorithms are no longer sufficient due to recent CNN architectures with additional parameters. This article presented a new

DA technique based on multimodal fusion (DAMF). In this study, which could combine the traditional DA method, data disrupting method, data mixing method, and auto adjustment method to enhance picture data in the training dataset and create new training images. Researchers also combined the classifier's outputs by voting on the basis of DAMF, which enhanced the results even more.

The accuracy rate from the research, "Pathological Myopia Image Recognition Strategy Based on Data Augmentation and Model Fusion", was calculated as the average accuracy rate obtained from 30 training epochs. The model training set's greatest accuracy was 100 percent. Table 2 shows the comparison of using DAMF against not using DAMF, with the original dataset as the 13th dataset. The results of all the datasets processed by DAMF were better than the 13th dataset's results, and the best DAMF corresponding to the first group of results is 2.84 percent higher than the 13th group, reaching 95.85 percent. This is a clear improvement. Additionally, AlexNet, GoogLeNet, and ResNet-50 have all been observed for the prediction accuracy improvement. The accuracy rates of these three models for training were 95.76 percent, 96.24 percent, and 95.60 percent, respectively.

Table 1. *Training Results* (Cui et al., 2021)

Table 2

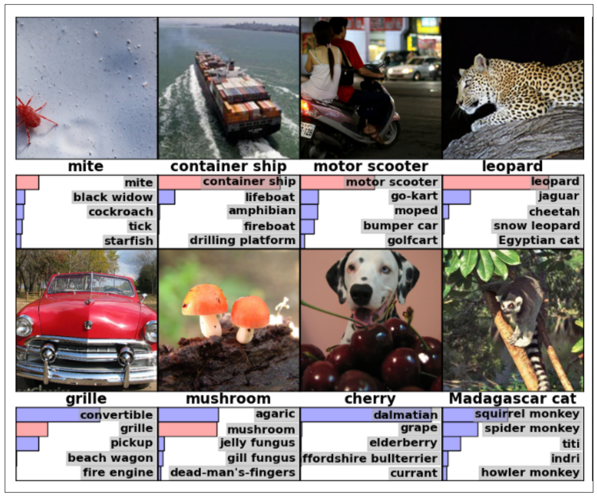
VGG-16 training results on 13 datasets.

No.	Dataset	Accuracy	Loss
1	PALM-Training1600-overturning-dimming-imgaug2	0.95858336	0.18674079
2	PALM-Training3200-overturning-noise-color-cropping-deforming-dimming	0.95550001	0.27185006
3	PALM-Training1600-overturning-cropping-deforming	0.95266668	0.16523545
4	PALM-Training800-color	0.95033336	0.17019135
5	PALM-Training800-dimming	0.94875002	0.17919912
6	PALM-Training800-cropping	0.94625	0.18303553
7	PALM-Training1600-overturning-dimming	0.94525003	0.23124305
8	PALM-Training1600-overturning-noise-color	0.94008333	0.21350351
9	PALM-Training800-overturning	0.93858335	0.20894363
10	PALM-Training800-deforming	0.93708334	0.20814224
11	PALM-Training800-noise	0.93608335	0.26124661
12	PALM-Training800-imgaug1	0.93391667	0.19876853
13	**PALM-Training400**	**0.93016667**	0.19310093

Based on the above, a 5-fold cross validation was used in this project in order to avoid over-fitting and to find the original misclassification. The results of the training on such images also extend the range of models used in the study. After culling, the VGG and ResNet models were finally selected for CNN training comparison.

According to Alex et al. ImageNet classification with deep convolutional ... - list of Proceedings, the research trained a large CNN to classify 1.2 million high-resolution images from the ImageNet LSVRC-2010 competition into 1000 different categories. And achieved top 1 and top 5 error rates in the test of 37.5% and 17.0% respectively, which is significantly better than the previous state-of-the-art (Krizhevsky et al., 2017).

Figure 1. *ILSVRC-2010 Test Results* (Krizhevsky et al., 2017)



With proven results and robust performance from this paper, CNN fits the need to train a large number of datasets from eight different sectors in CME's MSM within 10 years. As mentioned in the paper, this model offers many experimental options for setting the number of layers based on the needs, such as 16, 26, or higher layers. The ability of the CNN model to train images with high complexity strengthens the hypothesis that this method can handle MSM's dataset with lower complexity but high ambiguity at some sentiment states due to their slightly different nature of line direction.

According to Sim in Is Deep Learning for Image Recognition Applicable to Stock Market Prediction, the input variables are based on the closing prices of the respective time periods and the target variable is set to a value of 1 or 0. If the target value is 1, it means that the current closing price is higher than the previous time period (Sim et al., 2019).

Figure 2. *Technical indicator* (Sim et al., 2019)

$$\text{target} = \begin{cases} 0 & \textit{for close price}_t < \textit{close price}_{t-1} \\ 1 & \textit{for close price}_t \geq \textit{close price}_{t-1} \end{cases}$$

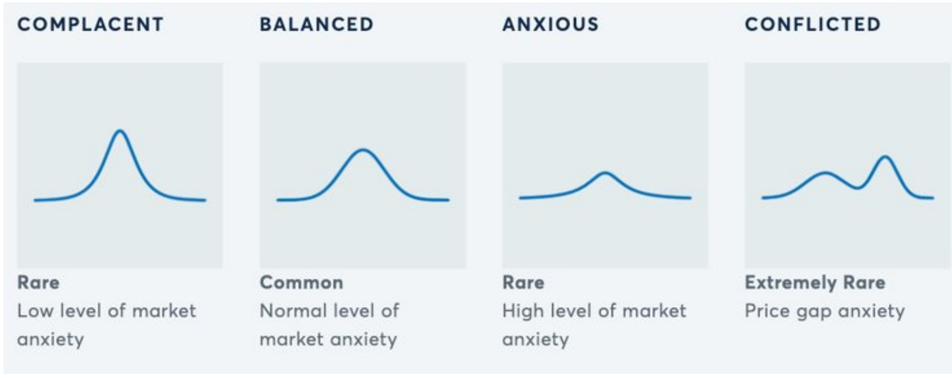
This technical specification inspired the project on Input Image Generation. Using a similar principle, CNN's Input Image Generation separates and connects 256 points with the same spacing. This turns the original 256-element distribution of data into an input image in terms of days, awaiting the next step of normalization.

In several studies during the literature review, CNN models have been shown to be effective for image classification. The prediction and classification of images based on Bimodal Distribution is not previously investigated. This research will focus on the reclassification and improvement of the original MSM tool based on CNN models.

Data

The MSM data comprises eight futures products (S&P E-mini, US 10-Year Treasuries, Gold, Euro-FX, WTI Crude Oil, Natural Gas, Corn, and Soybeans). Data is daily from January 2012, with settlement prices, high-low prices for the day, options implied volatility, put and call options volumes, and futures volumes. A wide variety of the metrics for volatility, momentum, and risk analysis are included in the data set. In addition, the data set includes a daily risk probability distribution with distributional metrics and a 256-element discreet distribution. The sentiment states of the distribution have been arbitrarily classified as complacent (Low level of market anxiety), balanced (Normal level of market anxiety), anxious (High level of market anxiety), and conflicted (bi-modal, Price gap anxiety).

Figure 3. *Four sentiment states*



Data Sources

The data sources, including eight different futures products (S&P E-mini, US 10-Year Treasuries, Gold, Euro-FX, WTI Crude Oil, Natural Gas, Corn, and Soybeans), are offered by CME Group. The team extract the 256-element discreet distribution for products. Below is the data frame information of corn future data.

Table 2. *Corn Future Data Frame Information*

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 256 entries, 0 to 255
Columns: 2589 entries, 20120103 to 20220411
dtypes: float64(2589)
```

Limitations of the data is that all data are given as data point. The model needs to generate the data automatically. Time window is from Jan 03, 2012, to Apr 11, 2022, a 10-year time window, comprised of 2589 rows.

Descriptive Analysis

The CNN is used to extract features of the original bi-modal distribution such as skewness, kurtosis and monotonicity. These are used as dependent variables.

The original data consisted of 4 states: Balanced with 14773, Anxious with 2842, complacent with 1873 and conflicted with 1224. Due to the imbalance in the distribution, the training set was rescaled before training. The rescaled data set has 2880 Balanced, 2842 Anxious, 1873 complacent and 1224 conflicted.

A total of 2668 distributions were reclassified after training, with the most notable transfer between the Anxious and Balanced states. The smaller proportion of reclassifications between Balanced or Complacent to Conflicted had a higher accuracy rate and corrected many of the previously obvious classification errors.

Table 3. *Result Distribution*

Anxious-Balanced	531
Balanced-Anxious	1355
Anxious-Complacent	268
Complacent-Anxious	417
Balanced-Conflicted	35
Anxious-Conflicted	33
Complacent-Conflicted	10
Conflicted-Anxious	2
Conflicted-Balanced	15
Conflicted-Complacent	2

Methodology

Feature Engineering

No feature engineering is required to further process the data from CME Group. Most deep learning models are able to perform some simple feature engineering tasks. These tasks include variable transformation and variable selection. The more important thing in Deep

Learning model is how models are built than a specific action, which makes feature engineering task less useful.

Another reason, in this case the team not directly use tabular data, instead the team extract image from those datasets. This situation leads to only use a single independent variable, not like a tabular data which have several features that needs to remove non-predictive features through feature engineering.

Modeling Frameworks

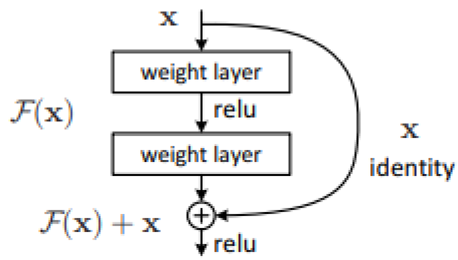
In the CNN model, two models are chosen and compared, VGG and ResNet, starting with VGG-16/19, and found that ResNet-152 was more accurate by large margin during the training process. VGG-16/19 has 15.3/19.6 billion FLOPS. ResNet-152 still has lower complexity than VGG-16/19.

Figure 4. *Resnet Frameworks* (He et al., 2016)

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

In ResNet model, to solve the problem of vanishing/exploding gradients, H(x)= F(x) + x. So, the weight learns this residual mapping: F(x)=H(x)-x.

Figure 5. Residual learning: a building block (He et al., 2016)



For the convolutional layer setting, the model only needs a single channel because the input data has only one colour. The kernel size is set to 7, the stride is 2, the number of paddings is 3, and the bias is False. In the specific train model setup, the batch size is 24 and the epoch is 30 in the 5-fold cross validation through iterative comparison. The batch size was set to 24 and the epoch to 30, and the batch size was set to 24 and the epoch to 12 when using the weight obtained from CV for weight selection and retraining. Under these conditions, both accuracy and loss rates levelled off and overfitting was avoided.

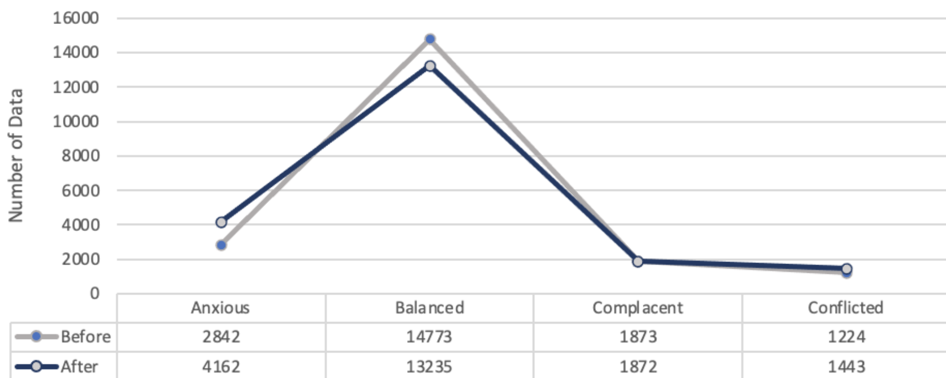
For the result, there are two ways to measure it. One is the rate of changes, with the ideal figure being around 10%. This way there is not too much data being reclassified. The second is the accuracy rate. However, because some of the original data was misclassified, this part requires random selection of the results and manual visual confirmation of the actual accuracy of the model.

Findings

The number of all after-model sentiment types increases, except for the Balanced, (dominating in 10% changes) and Complacent (1%) categories. This pattern indicates that most increasement in the other categories comes from Balanced sentiment. However, as shown in Figure

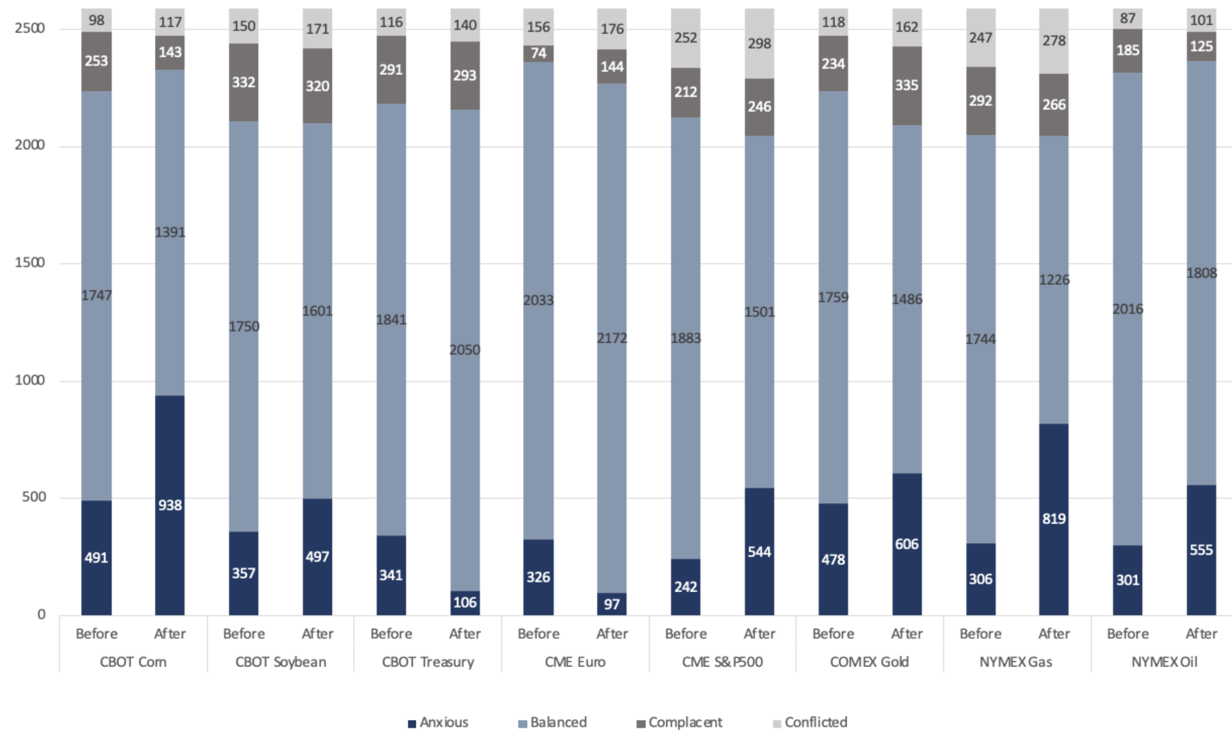
6, the highest number of sentiments is still Balanced state with decreasing value from 14,773 in the initial data to 13,235 after modeling.

Figure 6. *Comparison of Percentage Per Category: Before and After*



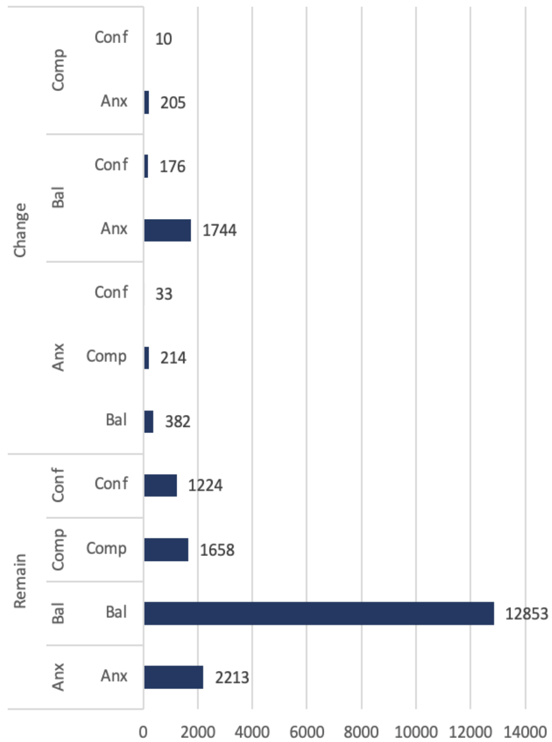
The model has done the work well by recategorizing the sentiments without deleting any of the data, the number of each category's dataset before and after the modeling process remains the same at 20,712 data. As seen in Figure 7, we can see how the model change states' composition in each product. Anxious state in some products changes drastically by more than |50%|, such as a 168% increase in NYMEX Gas and a decrease in CME Euro by -70%.

Figure 7. *Comparison of Category Changes in All Commodities: Before and After*



As seen in Figure 8, Only 13% of the data change their sentiments after the modelling process. Balanced to Anxious shifting dominates the change, while changes from Conflicted to other states do not appear. As many as 87% of the data remain the same as the initial category, with the highest number of sentiments being Balanced (64%), followed by Anxious (20%), Complacent (9%), and Conflicted (7%).

Figure 8. *Sentiment Changes*



Discussion

Although most distribution images are correctly transformed, 0.86-2.58% of the images are still incorrectly classified due to the limitations of the CNN model. However, as the stated problem in this research is reclassifying current incorrect market sentiment categories into new compositions, a good improvement over the original classification method was achieved without eliminating any states in the resulting model.

The team initially tried to mix LSTM and CNN models but found that LSTM is unsuitable for this kind of data because the results are not improved after mixing. Image recognition tools, especially CNNs, can extract features and classify them well for this type of data. Among all CNN models, the result shows that ResNet-152 is the most efficient model, achieving the highest correct rate. This is because this 152-layer model learns the residual representation function rather than the signal representation directly.

One of the significant challenges this project encounter is the normalization of the input images. However, it is prevalent for the image to be wrongly changed in this process, making some features disappear and thus reducing the accuracy. The datasets keep more non-zero parts to preserve these features as much as possible.

Due to the data imbalance and subtle features, the CNN model cannot extract some features. This algorithm used first-order and second-order derivative images to enhance these features. However, finding a common way to normalize the enhanced images took much work. The algorithm lastly uses the min-max function to alleviate this problem.

The CNN model is a black box, meaning the results don't tell exactly what features it extracts. Also, no direct access to the accuracy of the results it gives makes it difficult for the model to produce an exact accuracy. The approach is to select 100 randomly altered distributions and use the human eye to confirm that they are correctly classified, thus giving an approximate accuracy rate. With this current limitation to evaluating the model, future research on efficiently confirming the result in all datasets is needed, especially for a large number of data.

Recommendations

The result is a very good indicator of the future trend of the various market and guidelines for next-round asset management or investments. However, the team suggests manually combining the results with human judgment. The team believes each transaction for CME group is extremely important and has low tolerance of wrong decision. Depending too much on the algorithm, results sometimes could not indicate the real trend of the market and probably will let the company lose money.

The team believe this algorithm will be a great add-on of their original prediction method which could predict the trend more precisely and quickly. It will show the market change before some real events happen and the majority of the time, it should be correct.

In addition, the results show that the model can effectively understand the patterns of different states and can perform the classification more efficiently. It also corrects the misclassification of the original MSM and reclassifies some data according to features, allowing for a transition period between states. By observing the transition period, the user can predict the potential risk of the market in the future. This allows users to observe subtle changes in market sentiment more precisely.

For next step, the team thinking to enlarge accuracy and coverage of algorithm. A very good example will be to cover more alternative investment direction like private equity, venture capital and hedge fund. To show how the primary market react in the future and that could help trace the change in secondary market. Another direction is trying to improve original algorithm runs faster with more accuracy.

Conclusion

As we aim to make an image recognition model for reclassifying current market sentiment categories into new ones and applying it to the mercantile distribution graph as the input dataset, this model has achieved 97.42 ~ 99.14% in all products. Thus, this model will decrease the signal loss from the market and help investors make better judgments on their investment decisions.

By training using eight futures products (S&P E-mini, US 10-Year Treasuries, Gold, Euro-FX, WTI Crude Oil, Natural Gas, Corn, and Soybean), the image recognition model increases the accuracy of state classification of these financial products by 10.42 ~ 12.14%. This proves that the image recognition algorithm as one of the Machine Learning methods can help the existing MSM classification model to work better. As a result, image recognition can work in conjunction with the current MSM model to improve its accuracy of market sentiment state classifications even further.

Reference

Cohen, N., Balch, T., & Veloso, M. (2020, October 15). *Trading via image classification* . arxiv.org. Retrieved April 26, 2022, from https://arxiv.org/pdf/1907.10046.pdf

Cui, J., Zhang, X., Xiong, F., & Chen, C.-L. (2021, May 6). *Pathological myopia image recognition strategy based on data augmentation and model fusion*. Journal of Healthcare Engineering. Retrieved April 25, 2022, from https://www.hindawi.com/journals/jhe/2021/5549779/

He, K., Zhang, X., Ren, S., & Sun, J. (2016, January 1). *Deep residual learning for image recognition*. Page Redirection. Retrieved October 24, 2022, from https://www.cv-foundation.org/openaccess/content_cvpr_2016/html/He_Deep_Residual_Learning_CVPR_2016_paper.html

Islam, M. Z., Islam, M. M., & Asraf, A. (2020, August 15). *A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images*. Informatics in Medicine Unlocked. Retrieved April 25, 2022, from https://www.sciencedirect.com/science/article/pii/S2352914820305621

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). *ImageNet classification with deep convolutional ... - neurips*. neurips.cc. Retrieved April 26, 2022, from https://proceedings.neurips.cc/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf

Lin, Y., Liu, S., Yang, H., Wu, H., & Jiang, B. (2021, August 6). *Improving stock trading decisions based on pattern recognition using machine learning technology*. PLOS ONE. Retrieved April 25, 2022, from https://journals.plos.org/plosone/article?id=10.1371%2Fjournal.pone.0255558

Sim, H. S., Kim, H. I., & Ahn, J. J. (2019, February 19). *Is deep learning for image recognition applicable to stock market prediction?* Complexity. Retrieved April 25, 2022, from https://www.hindawi.com/journals/complexity/2019/4324878/

Velay, M., & Daniel, F. (2018, June). *Stock chart pattern recognition with deep learning - arxiv*. arxiv.org. Retrieved April 26, 2022, from https://arxiv.org/pdf/1808.00418.pdf

Wang, H., Wang, J., Cao, L., Li, Y., Sun, Q., & Wang, J. (2021, September 22). *A stock closing price prediction model based on CNN-BISLSTM*. Complexity. Retrieved April 25, 2022, from https://www.hindawi.com/journals/complexity/2021/5360828/

Appendix A: List of Figures

Figure 1. *ILSVRC-2010 Test Results* (Krizhevsky et al., 2017)

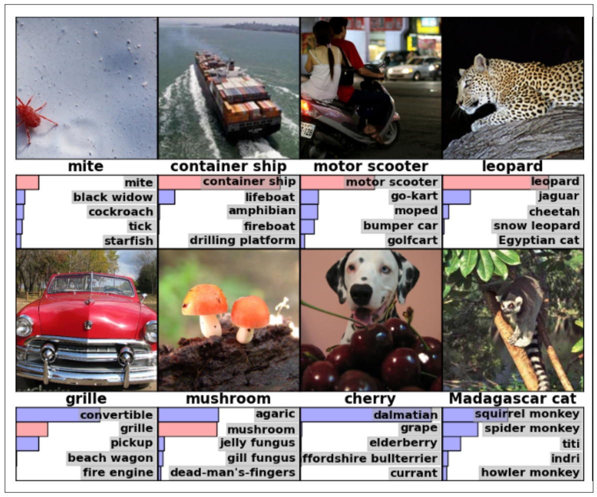


Figure 2. *Technical indicator* (Sim et al., 2019)

$$\text{target} = \begin{cases} 0 & \textit{for close price}_t < \textit{close price}_{t-1} \\ 1 & \textit{for close price}_t \geq \textit{close price}_{t-1} \end{cases}$$

Figure 3. *Four sentiment states*

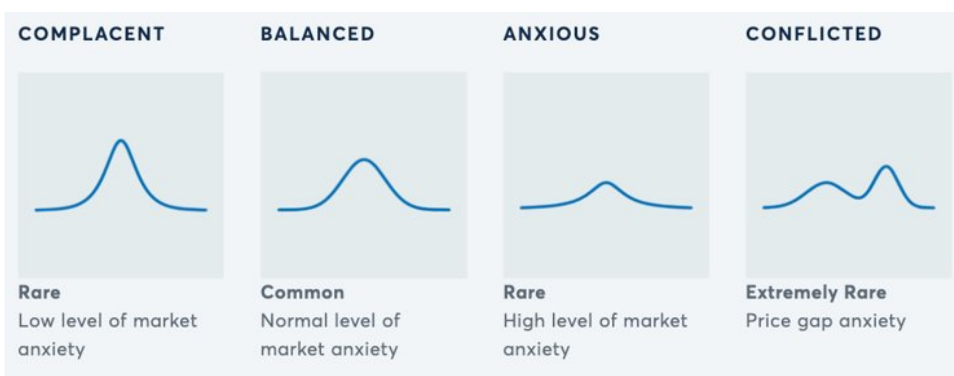


Figure 4. *Resnet Frameworks* (He et al., 2016)

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
		3×3 max pool, stride 2				
conv2_x	56×56	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times23$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Figure 5. Residual learning: a building block (He et al., 2016)

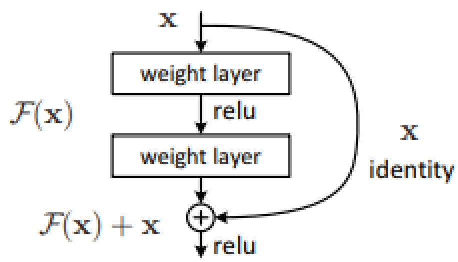


Figure 6. *Comparison of Percentage Per Category: Before and After*

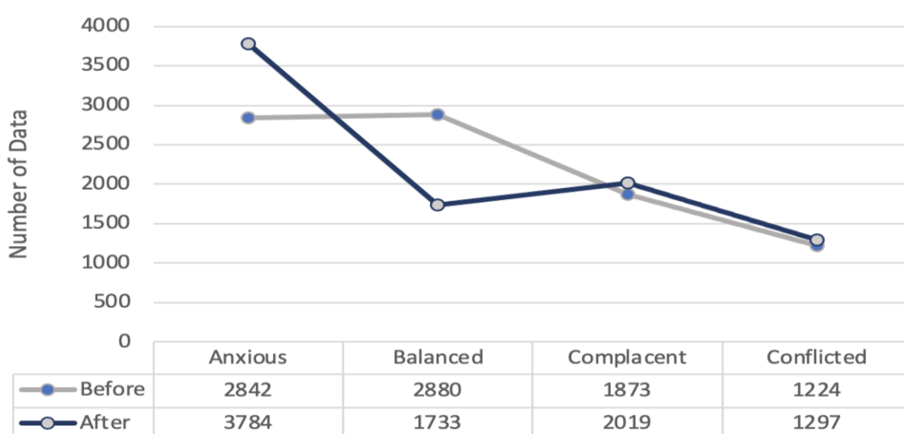


Figure 7. *Comparison of Category Changes in All Commodities: Before and After*

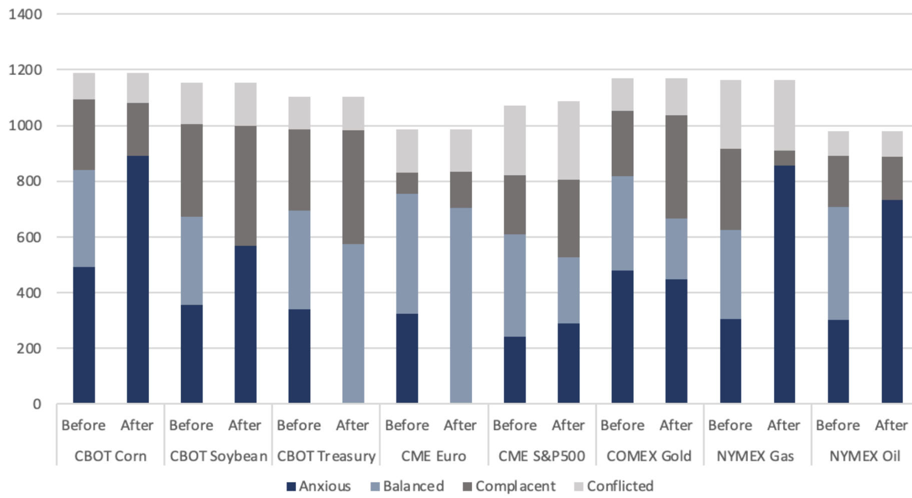
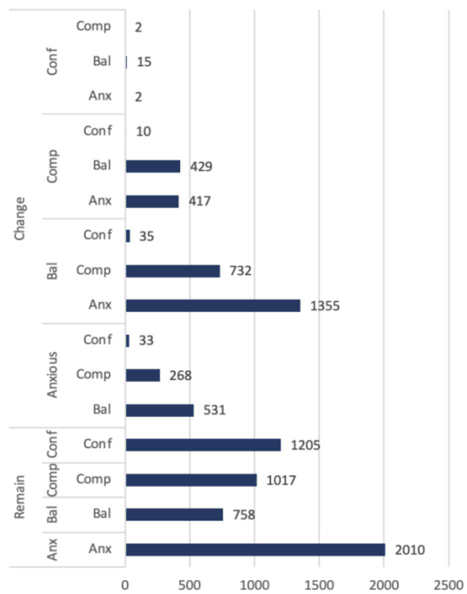


Figure 8. *Sentiment Changes*



Appendix B: List of Tables

Table 1. *Training Results* (Cui et al., 2021)

Table 2

VGG-16 training results on 13 datasets.

No.	Dataset	Accuracy	Loss
1	PALM-Training1600-overturning-dimming-imgaug2	0.95858336	0.18674079
2	PALM-Training3200-overturning-noise-color-cropping-deforming-dimming	0.95550001	0.27185006
3	PALM-Training1600-overturning-cropping-deforming	0.95266668	0.16523545
4	PALM-Training800-color	0.95033336	0.17019135
5	PALM-Training800-dimming	0.94875002	0.17919912
6	PALM-Training800-cropping	0.94625	0.18303553
7	PALM-Training1600-overturning-dimming	0.94525003	0.23124305
8	PALM-Training1600-overturning-noise-color	0.94008333	0.21350351
9	PALM-Training800-overturning	0.93858335	0.20894363
10	PALM-Training800-deforming	0.93708334	0.20814224
11	PALM-Training800-noise	0.93608335	0.26124661
12	PALM-Training800-imgaug1	0.93391667	0.19876853
13	**PALM-Training400**	**0.93016667**	0.19310093

Table 2. *Corn Future Data Frame Information*

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 256 entries, 0 to 255
Columns: 2589 entries, 20120103 to 20220411
dtypes: float64(2589)
```

Table 3. *Result Distribution*

```
Anxious-Balanced       531
Balanced-Anxious       1355
Anxious-Complacent     268
Complacent-Anxious     417
Balanced-Conflicted    35
Anxious-Conflicted     33
Complacent-Conflicted  10
Conflicted-Anxious     2
Conflicted-Balanced    15
Conflicted-Complacent  2
```