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# Improving Heikin-Ashi Transformation Data Learning in Neural Network Using Volume Weight in Stock Market Data

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## ABSTRACT

This paper provides a further analysis and improvement of Heikin Ashi Transformation for Neural Network Learning. It has been demonstrated that Heikin Ashi Transformation can improve the learning effect of Neural Network. This paper introduces another improvement using volume-weighted data for learning and its effect for neural network learning process.
**Keywords:** Heikin Ashi Transformation, Neural Network, Stock Market Analysis, Time series filtering

## I. INTRODUCTION

The machines and information have commanded present time. As the power of calculation heightened towards sky, we were able to make better framework that can harness this computational power and transform them into complex framework. The craft of examining information is extremely valuable. The information itself is futile, unless we can locate some hidden patterns or data inside. High power machine can turn this data into recognizable patterns far better now. Recognizing patterns among information is a key variable in modern research. Since we have enough computational power available to us, we would device techniques that enable machine to analyse data patterns and discover under lying information.

Neural network provide an excellent way to mimic human brain and allow machine to learn underlying patterns. Given a sufficient large training data, neural network can learn it propeties and make prediction based on the learning (Guresen et al., 2011). One of the most promising fields of such research includes finance. Stock market is a very dynamic place. stock market data patterns hold a key in finance research. Such finance patterns allow institutions to make better decision. But stock market data can contain unwanted noise. Noise can be a short term fluctuation in stock market data. Such Noise is undesired within the data and may or may not be related to the underlying stock data trend. We have already demonstrated that such noise can interfere with learning of neural network and hence reduces the effectiveness of learning and its effectiveness. The Heikin-Ashi transformation has worked remarkably well reducing noise and its effect can be further improved using volume weighted data, which adds another piece of information for better noise reduction.

The Sources of noise can be many. Such noises are result of market overreaction to viral news outbreak (Howe, 1986) and other factors such as short term traders exiting their positions far too early. Filtering of training data has been suggested by many authors.

The use of Kalman filters has proved to be effective in signal processing (Haykin, 2001) (Wan and Merwe, 2000) it has been observed that such filters improve the effectiveness of underlying system. Researchers have used wavelet transformation for neural network (Hosseinioun, 2016) and improved the learning and prediction results. Many optimization have been suggested to improve the performance and accuracy of neural network (Qiu and Song, 2016) including modular neural network (Kimoto et al., 1990). This strongly suggests that data filtering can benefit a neural networks performance. Researcher have already suggested that noise interferes with learning and hence the prediction rate declines (Adam et al., 2016). Neural network performance can be easily measured in percentage accuracy as discussed by researchers (Brownstone, 1996) this simple approach provides a better way to test an compare two different data filtering techniques . The concept of transformation is heavily used in signal processing as demonstrated by researchers (Kuan et al., 1985) in signal processing. Beals smoothing function for community analysis ("Improving community analysis with the Beals smoothing function: Écoscience: Vol 1, No 1," n.d.) further supports the fact that a given system may require transformation for better reliability. The wavelet transformation in ECG system has been proven to be beneficial as suggested by authors (Sahambi et al., 1997). A least square method has been suggested in improving signal to noise ratio as demonstrated by C.G. Enke & Timothy A Nieman (Enke and Nieman, 1976).

## II. METHODS AND MATERIAL

In our previous paper we defined smoothing of stock data using Heikin-Ashi Transformation for Stock market. Heikin-Ashi is widely used in candlestick charts. In Japanese, Heikin means "average" and "Ashi" means "pace". Since it is based on candlestick patterns. We give a brief intro to candlesticks.

A candlestick describes trade information of a given time period. Every candlestick has 4 values Open, High, Low and Close. These values represent the value at which stock or index candle opened, highest value of stock, lowest value of stock and closing value of the stock in that time period.

Heikin-Ashi transforms these 4 values using following formulas to create new candlesticks. New Candlestick produces simpler and smoother candlestick for analysis.

**Transformation rules:**

Let $O_{current}$, $H_{current}$ , $L_{current}$, $C_{current}$ represents current open, high, low, close values.

Let $O_{Prev}$, $H_{Prev}$, $L_{Prev}$, $C_{Prev}$ represents Previous day/period open, high, low, close values.

Then Heikin-Ashi values (HA) are calculated as:-

HA-Close = ($O_{current}$ + $H_{current}$ +$L_{current}$+$C_{current}$)/ 4

HA-Open = (HA-$Open_{Prev}$ + HA-$Close_{Prev}$) / 2

HA-High = Maximum of the $H_{current}$ , HA-Open or HA-Close

HA-Low = Minimum of the $L_{Current}$ , HA-Open or HA-Close

**Normal Candlesticks**


Above image, demonstrate the smoothing effect produced by Heikin Ashi Transformation.

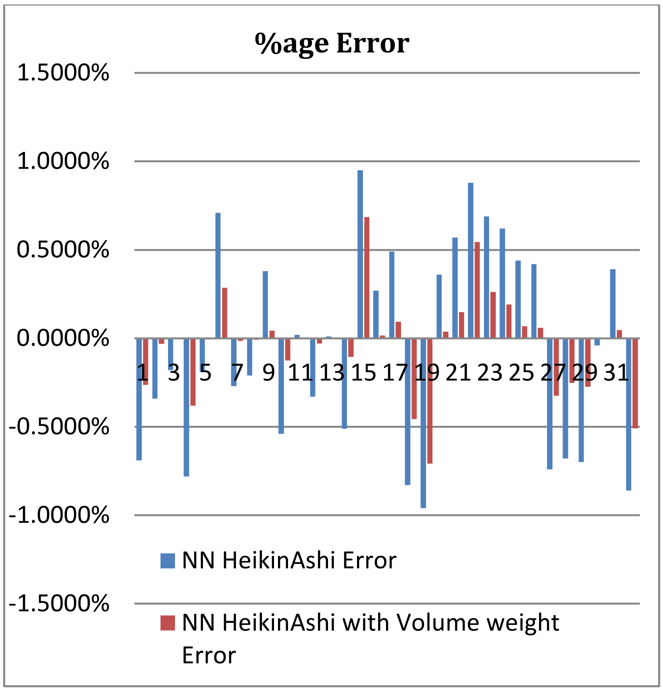
**Introducing Volume Weight:**

The core idea is to use volume as a gauge to measure the sentiment behind a candlestick move. More volume signifies more participation in the given move and hence must be introduce into learning of Neural Network. Main Idea is to normalize Volume data over a time period to a set of [0,1] and then use that as an additional input for learning.

**Setup:**

The setup consists of creating a 2 hidden layer neural network with 5,6,3,1 layer configuration. The Test data is converted into 2 sets. One set is for learning, other set is for testing. Following results were observed.

| | NN with HeikinAshi | NN HeikinAshi with Volume weight Error |
|---|---|---|
| Average | 0.022% | 0.007% |
| STD Dev | 0.654% | 0.363% |




**Result Skew:**

A result skew is observed after a series of consecutive data inputs. The skew signifies recalibration of the Neural network to fit the current scenario environment.

## III. CONCLUSION

We see a significant reduction in false positives using volume weight as input during learning. However the results tend to skew after long duration and a calibration is needed after sometimes. But again results are encouraging for further investigating and improving this scheme.

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