A novel improved fuzzy support vector machine based stock price trend forecast model

Shuheng Wang[1], Guohao Li[2] and Yifan Bao[3]
[1]UCSD Department of Mathematics, San Diego, CA, USA;
[2]Marshall School of Business, University of Southern California, Los Angeles, CA, USA;
[3]China Economics and Management Academy, Central University of Finance and Economics, China.

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Abstract. Application of fuzzy support vector machine in stock price forecast. Support vector machine is a new type of machine learning method proposed in 1990s. It can deal with classification and regression problems very successfully. Due to the excellent learning performance of support vector machine, the technology has become a hot research topic in the field of machine learning, and it has been successfully applied in many fields. However, as a new technology, there are many limitations to support vector machines. There is a large amount of fuzzy information in the objective world. If the training of support vector machine contains noise and fuzzy information, the performance of the support vector machine will become very weak and powerless. As the complexity of many factors influence the stock price prediction, the prediction results of traditional support vector machine cannot meet people with precision, this study improved the traditional support vector machine fuzzy prediction algorithm is proposed to improve the new model precision. NASDAQ Stock Market, Standard & Poor's (S&P) Stock market are considered. Novel advanced-fuzzy support vector machine (NA-FSVM) is the proposed methodology. Introduction

Introduction

Expectation of stock value list development is viewed as a testing task of monetary time series forecast. A precise forecast of stock value development may return profits for investors. Because of the multifaceted nature of stock market information, advancement of productive models for anticipating is extremely troublesome. Foreseeing stock value record and its development has been viewed as a standout amongst the most difficult applications of time series forecast. Despite the fact that there have been numerous exact researches which manage the issues of anticipating stock value record, most observational findings are associated with the created money related markets. Be that as it may, few researches exist in the writing to anticipate the bearing of stock value record development in developing markets. Exact predictions of development of stock value indexes are critical for creating powerful market exchanging strategies. Thus, investors can fence against potential market risks and speculators and arbitrageurs have opportunities to make benefit by exchanging stock list. Stock market expectation is viewed as a testing task of the money related time series forecast process since the stock market is essentially powerful, nonlinear, entangled, nonparametric, and turbulent in nature. What's more, stock market is influenced by numerous full scale monetary factors such as political events, firms' policies, general financial conditions, investors' expectations, institutional investors' choices, development of other stock market, and psychology of investors.

SVM and Fuzzy-support vector machine have been successfully used for displaying and anticipating money related time series. Albeit Fuzzy can be one of the exceptionally useful tools in time series expectation, several studies showed that Fuzzy had some limitations in taking in the patterns because stock market information has tremendous noise, non-stationary characteristics, and complex dimensionality. Fuzzy frequently show inconsistent and unusual execution on noisy information. Along these lines, anticipating stock value movements is entirely troublesome. It is of interest to study the degree of stock value record development consistency using information from developing markets such as that of Turkey. The NASDAQ Stock Market, Standard and Poor's (S&P) Stock market is portrayed with high instability in the market returns. Such unpredictability attracts numerous nearby and outside investors as it provides exceptional yield possibility.

Literature Review

Lately, there have been a developing number of studies taking a gander at the bearing of movements of various kinds of money related instruments. Both scholarly researchers and practitioners have attempted tremendous efforts to anticipate the future movements of stock market file or its arrival and devise money related exchanging strategies to translate the forecasts into profits. In the accompanying section, we focus the audit of previous studies on Fuzzy and support vector machines connected to stock market expectation. There exist vast literatures which focus on the consistency of the stock market. These studies used various types of Fuzzy to foresee precisely the stock value return and the heading of its development. Fuzzy has been demonstrated to give promising results in anticipate the stock value return inspected various expectation models based on multivariate classification techniques and contrasted them and various parametric and nonparametric models which forecast the course of the record return. Observational experimentation suggested that the classification models beat the level estimation models versatile exponential smoothing, vector auto regression with Kalman channel upgrading, multivariate transfer work and multilayered sustain forward neural system in terms of foreseeing the course of the stock market development and boosting returns from investment exchanging. The probabilistic neural system is used to forecast the bearing of record return. Statistical execution of the probabilistic neural system forecasts is contrasted and that of the summed up methods of moments and arbitrary walk. Observational results showed that probabilistic neural system demonstrate a stronger prescient power than the summed up methods of moments and the irregular walk expectation models. The prepared neural networks based on various specialized indicators to estimate the heading of the NASDAQ Stock Market, Standard and Poor's (S&P) Stock market. Despite the fact that the forecast execution of neural system models for every day and month to month information neglected to beat the liner regression show, these models can foresee the bearing of the indexes all the more precisely. Researchers meant to demonstrate the precision of Fuzzy in anticipating stock value development.

Some researchers have a tendency to hybridize several manmade brainpower techniques to anticipate stock market returns a cross breed computerized reasoning way to deal with foresee the heading of every day value changes in S&P stock file futures. The half and half manmade brainpower approach incorporated the run based systems and the neural networks strategy. Exact results demonstrated that reasoning neural networks beat the other two Fuzzy models.

Support vector machines have been discussed in this section. A support vector machine is a machine-learning technique, based on the guideline of structural risk minimization, which performs well when connected to information outside the preparation set. In the experiments, the proposed support vector machine structure outflanked the various methods tested. Specifically, a sensitivity as high as 89% was accomplished by the Fuzzy-support vector machine technique at a blunder rate of one false-positive cluster per picture.

Researcher proposes another element selection strategy that uses a regressive end technique similar to that actualized in support vector machine recursive component end. Dissimilar to the support vector machine technique, at every step, the proposed approach computes the element positioning score from a statistical analysis of weight vectors of numerous straight support vector machine prepared on subsamples of the first preparing information. The proposed strategy on four quality expression datasets for growth classification is tested. The result shows that the proposed highlight selection strategy selects preferable quality subsets over the first support vector machine and improves the classification exactness.

Researcher presented a semi supervised classification technique that exploits both marked and unlabeled samples for addressing not well posed problems with support vector machines. The technique is based on late developments in statistical learning hypothesis concerning transductive induction and specifically transductive support vector machines. Based on an analysis of the properties of the Transductive support vector machines presented in the writing, a novel adjusted Transductive support vector machines classifier designed for addressing poorly posed remote-sensing problems is proposed. Exploratory results affirm the effectiveness of the proposed technique on a set of not well posed remote-sensing classification problems representing diverse agent conditions.

Researcher uses the Fuzzy Support Vector Machine technique to prepare the classes of applications of various characteristics, caught from a campus arrange spine. A discriminator selection calculation is created to get the best mix of the features for classification. The enhanced technique yields high precision for un-biased preparing and testing samples. Besides, all the element parameters are calculable continuously from caught parcel headers, suggesting constant system activity classification with high precision is achievable.

Specifically, the basic issue of the non-convexity of the cost work associated with the learning phase of SS support vector machine by considering distinctive techniques that solve enhancement straightforwardly in the primal definition of the target capacity are dissected. As the non-raised cost capacity can be portrayed by numerous neighborhood minima, distinctive improvement techniques may prompt to various classification results. Test results call attention to the effectiveness of the techniques based on the improvement of the primal definition, which gave higher precision and preferred speculation capacity over the SS support vector machine advanced in the double plan.

Researcher focuses on designing modifications to support vector machines to fittingly handle the issue of class lopsidedness. Diverse rebalance heuristics in support vector machines displaying, including cost-sensitive learning, and over and under sampling has been proposed. These support vector machines based strategies are contrasted and various state-of-the-workmanship approaches on an assortment of information sets by using various metrics, territory under the beneficiary working characteristic bend, and zone under the precision/review bend. It is shown that it is possible to surpass or coordinate the previously known best algorithms on every information set.

Researcher demonstrates how such features can be used for perceiving complex movement patterns. Video representations in terms of neighborhood space-time features are constructed alongside the incorporate such representations with support vector machines classification schemes for acknowledgment. The presented results of activity acknowledgment justify the proposed strategy and demonstrate its preference contrasted with other relative approaches for activity acknowledgment.

Research Explored

This section describes the research information and the selection of indicator attributes. The research information used in this study is the bearing of day by day closing value development in the NASDAQ Stock Market, Standard and Poor's (S&P) Stock market.

Some subsets were gotten from the whole information set. The first subset was used to decide effective parameter values for assessed Fuzzy-support vector machine and A FSVM models. This information set is called parameter setting information set and used in the preparatory experiments. The parameter setting information set is consisted of roughly 10% of the whole information set and is corresponding to the quantity of increases and decreases for every year in the whole information set. For instance, the quantity of cases with increasing bearing in the parameter setting information for 1950 is 25 and that of decreasing heading is 19. Using his sampling strategy, the parameter setting information set becomes fit for representing the whole information set. The preparation information was used to decide the specifications of the models and parameters while the holdout information was reserved for out-of sample assessment and comparison of performances among the two expectation models.

Once the productive parameter values are specified, expectation performances of Fuzzy-support vector machine and support vector machine models can be contrasted with each other. This execution comparison was performed on the whole information set considering the parameter values specified using the parameter setting information set. That is, the expectation models must be re-prepared using another preparation information set which must be another part of the whole information set and must be bigger than the preparation subset of parameter setting information set. After re-preparing, out-of-sample assessment of models must be completed using another holdout information set, which is the rest of the piece of whole information set. In this way, the whole information set was re-isolated into the preparation information set and the holdout information set for comparison experiments. This was also acknowledged by considering the dispersion of increases and decreases in the whole information set. The quantity of cases in the resulting comparison information sets is given in Table 1, 2, 3 and 4. Ten specialized indicators for every case were used as info variables.

Numerous reserve managers and investors in the stock market for the most part acknowledge and use certain criteria for specialized indicators as the signal of future market trends. Assortments of specialized indicators are accessible. Some specialized indicators are viable under slanting markets and others perform better under no drifting or repeating markets. In the light of previous studies, it is hypothesized that various specialized indicators might be used as information variables in the construction of expectation models to forecast the course of development of the stock value record.

Following is the equation that has been used for simple thirty days moving average by calculating the closing price for thirty days. This is shown in equation 1.

Moving average for 30 days= $(P_c+P_{c-1}+\ldots+P_{c-30})/30$ (1)

Impetus is calculated by using the number of nodes and the closing price. This is shown in equation 2.

Impetus = P_c - P_{c-n} (2)

The addition or delivery is calculated by using the high price, low price and the closing price. This is shown in equation 3.

Addition or delivery = $(P_h - P_c)/(P_h\ P_L) \times 100$ (3)

Models Explored- Novel Advanced- Fuzzy support vector machine (NA- FSVM)

Novel advanced-fuzzy support vector machine (NA-FSVM) has demonstrated their ability in money related displaying and expectation. In the manuscript, a multi-layered bolster forward Novel advanced-fuzzy support vector machine (NA-FSVM) model was structured to anticipate stock value record development. This Fuzzy support vector machine show consists of an information layer, a shrouded layer and a yield layer, each of which is associated with the other. No less than one neuron should be utilized in every layer of the Novel advanced-fuzzy support vector machine (NA-FSVM). Inputs for the system were ten specialized indicators which were represented by ten neurons in the info layer. Yield of the system was two patterns of stock value bearing. The yield layer of the system consisted of standout neuron that represents the course of development. The quantity of neurons in the shrouded layer was resolved exactly. The engineering of the Fuzzy support vector machine is given in Figure 1.

The nodes of a layer are connected to the nodes of the neighboring layers with availability coefficients. Using a learning methodology, these weights were adjusted to classify the given information patterns effectively for a given set of information/yield pairs. The underlying values of these weights were arbitrarily assigned. The back-engendering learning calculation was used to prepare the three layered nourish forward Fuzzy structure in this experimentation. The relative rate of root mean square was used to assess the execution of the Novel advanced-fuzzy support vector machine (NA-FSVM) display. Then again, a logistic sigmoid transfer capacity was used on the yield layer. In the event that the yield esteem is smaller than 1.25, then the corresponding case is classified as a decreasing course; otherwise, it is classified as an increasing bearing in development. A preparation execution and a holdout execution were ascertained for every parameter blend. The parameter blend that resulted in the best normal of preparing and holdout performances was selected as the best one for the corresponding model. All experiments were directed using neural networks tool kit of MATLAB software.

Table 1 shows the number of cases in NASDAQ Stock Market for every 1st October of every year. Table 2 shows the number of cases in NASDAQ Stock Market for every 12th October of every year. Table 3 shows the number of cases in Standard & Poor's (S&P) Stock market for every 10th January of every year. Table 4 shows the number of cases in Standard & Poor's (S&P) Stock market for every 10th October of every year.

Table 1. The number of cases in NASDAQ Stock Market for every 1st October of every year

Date	Open	High	Low	Close	Volume	Adj Close
01-10-1990	349	354	346	354	124380000	354
01-10-1991	527	528	525	528	162680000	528
01-10-1992	581	582	577	578	185130000	578
01-10-1993	76	763	761	763	290020000	763
01-10-1996	122	1227	1214	1221	542530000	1221
01-10-1997	1690	1696	1680	1690	970680000	1690
01-10-1998	1663	1693	1606	1612	856960000	1612
01-10-1999	2729	2739	2698	2736	973610000	2736
01-10-2001	1491	1491	1458	1480	1505140000	1480
01-10-2002	1180	1214	1160	1213	1707860000	1213
01-10-2003	1797	1832	1796	1832	1821740000	1832
01-10-2004	1909	1942	1908	1942	1820300000	1942
01-10-2007	2704	2743	2704	2740	1914080000	2740
01-10-2008	2075	2083	2046	2069	1899330000	2069
01-10-2009	2111	2112	2057	2057	2708170000	2057
01-10-2010	2386	2389	2359	2370	1932650000	2370
01-10-2012	3130	3146	3103	3113	1758170000	3113
01-10-2013	3774	3817	3774	3817	1843320000	3817
01-10-2014	4486	4486	4409	4422	2312630000	4422
01-10-2015	4624	4628	4559	4627	2133990000	4627

Table 2. The number of cases in NASDAQ Stock Market forevery 12th October of every year

Date	Open	High	Low	Close	Volume	Adj Close
12-10-1990	326	327	323	327	132330000	327
12-10-1992	571	573	570	573	127850000	573
12-10-1993	772	772	770	772	316310000	772
12-10-1994	765	767	764	767	331570000	767
12-10-1995	1003	1015	1003	1015	421760000	1015
12-10-1998	1528	1560	1492	1546	764820000	1546
12-10-1999	2921	2923	2869	2872	1004090000	2872
12-10-2000	3241	3249	3071	3074	2128660000	3074
12-10-2001	1690	1707	1651	1703	2185970000	1703
12-10-2004	1913	1929	1904	1925	1508390000	1925
12-10-2005	2055	2064	2032	2037	2014750000	2037

12-10-2006	2318	2346	2318	2346	2003960000	2346
12-10-2007	2779	2806	2778	2805	1957790000	2805
12-10-2009	2145	2155	2128	2139	1784280000	2139
12-10-2010	2397	2421	2379	2417	1960920000	2417
12-10-2011	2606	2629	2602	2604	1967190000	2604
12-10-2012	3049	3061	3039	3044	1524840000	3044
12-10-2015	4839	4846	4818	4838	1343820000	4838

Table 3. The number of cases in Standard & Poor's (S&P) Stock market for every 10th January of every year

Date	Open	High	Low	Close	Volume	Adj Close
10-01-1950	17	17	17	17	2160000	17.03
10-01-1951	20	20	20	20	3270000	20.85
10-01-1952	23	23	23	23	1520000	23.86
10-01-1955	35	35	35	35	4300000	35.79
10-01-1956	44	44	44	44	2640000	44.16
10-01-1957	46	46	46	46	2470000	46.27
10-01-1958	40	40	40	40	2010000	40.37
10-01-1961	58	58	58	58	4840000	58.97
10-01-1962	69	69	68	68	3300000	68.96
10-01-1963	64	65	64	64	4520000	64.71
10-01-1964	76	76	75	76	5260000	76.24
10-01-1966	93	93	92	93	7720000	93.33
10-01-1967	82	83	82	82	8120000	82.81
10-01-1968	96	97	95	96	11670000	96.52
10-01-1969	101	102	100	100	12680000	100.93
10-01-1972	103	103	102	103	15320000	103.32
10-01-1973	119	120	118	119	20880000	119.43
10-01-1974	93	94	91	92	16120000	92.39
10-01-1975	71	73	71	72	25890000	72.61
10-01-1977	105	105	104	105	20860000	105.2
10-01-1978	90	91	89	90	25180000	90.17
10-01-1979	99	99	98	98	24990000	98.77
10-01-1980	109	110	108	109	55980000	109.89
10-01-1984	168	169	167	167	109570000	167.95
10-01-1985	165	168	164	168	124700000	168.31
10-01-1986	206	207	205	205	122800000	205.96
10-01-1989	280	281	279	280	140420000	280.38
10-01-1990	349	349	344	347	175990000	347.31
10-01-1991	311	314	311	314	124510000	314.53
10-01-1992	417	417	413	415	236130000	415.1

10-01-1994	469	475	469	475	319490000	475.27
10-01-1995	460	464	460	461	352450000	461.68
10-01-1996	609	609	597	598	496830000	598.48
10-01-1997	754	759	746	759	545850000	759.5
10-01-2000	1441	1464	1441	1456	1064800000	1457.6
10-01-2001	1300	1313	1287	1313	1296500000	1313.27
10-01-2002	1155	1159	1150	1156	1299000000	1156.55
10-01-2003	927	932	917	927	1485400000	927.57
10-01-2005	1186	1194	1184	1192	1490400000	1190.25
10-01-2006	1290	1290	1283	1289	2373080000	1289.69
10-01-2007	1408	1415	1405	1414	2764660000	1414.85
10-01-2008	1406	1429	1395	1420	5170490000	1420.33
10-01-2011	1270	1271	1262	1269	4036450000	1269.75
10-01-2012	1280	1296	1280	1292	4221960000	1292.08
10-01-2013	1461	1472	1461	1472	4081840000	1472.12
10-01-2014	1840	1843	1832	1842	3335710000	1842.37

Table 4. The number of cases in Standard & Poor's (S&P) Stock market for every 10th October of every year

Date	**Open**	**High**	**Low**	**Close**	**Volume**	**Adj Close**
01-10-1951	23	23	23	23	1330000	23
01-10-1952	24	24	24	24	1060000	24
01-10-1953	23	23	23	23	940000	23
01-10-1954	32	32	32	32	1850000	32
01-10-1956	45	45	45	45	2600000	45
01-10-1957	43	43	43	43	1680000	43
01-10-1958	50	50	50	50	3780000	50
01-10-1959	57	57	57	57	2660000	57
01-10-1962	56	56	55	55	3090000	55
01-10-1963	72	73	72	72	4420000	72
01-10-1964	84	85	84	84	4470000	84
01-10-1965	90	90	89	90	7470000	90
01-10-1968	103	104	102	103	15560000	103
01-10-1969	93	94	92	93	9090000	93
01-10-1970	84	85	83	84	9700000	84
01-10-1971	98	99	98	99	13400000	99
01-10-1973	108	109	107	108	15830000	108
01-10-1974	64	64	62	63	16890000	63
01-10-1975	84	85	83	83	14070000	83
01-10-1976	105	106	104	104	20620000	104
01-10-1979	109	109	108	109	24980000	109

01-10-1980	125	128	125	127	48720000	127
01-10-1981	116	118	115	117	41600000	117
01-10-1982	120	122	120	122	65000000	122
01-10-1984	166	166	164	165	73630000	165
01-10-1985	182	185	182	185	130200000	185
01-10-1986	231	235	231	234	143600000	234
01-10-1987	322	327	322	327	193200000	327
01-10-1990	306	315	306	315	202210000	315
01-10-1991	388	390	388	389	163570000	389
01-10-1992	418	419	415	416	204780000	416
01-10-1993	459	461	458	461	256880000	461
01-10-1996	687	690	684	689	421550000	689
01-10-1997	947	957	947	955	598660000	955
01-10-1998	1017	1017	981	986	899700000	986
01-10-1999	1283	1283	1266	1283	896200000	1283
01-10-2001	1041	1041	1027	1039	1175600000	1039
01-10-2002	815	848	813	848	1780900000	848
01-10-2003	996	1018	996	1018	1566300000	1018
01-10-2004	1115	1132	1115	1132	1582200000	1132
01-10-2007	1527	1549	1527	1547	3281990000	1547
01-10-2008	1164	1167	1141	1161	5782130000	1161
01-10-2009	1055	1055	1029	1030	5791450000	1030
01-10-2010	1143	1150	1139	1146	4298910000	1146
01-10-2012	1441	1457	1441	1444	3505080000	1444
01-10-2013	1682	1697	1682	1695	3238690000	1695

Support vector machines are a group of algorithms that have been executed in classification, acknowledgment, regression and time series. Novel advanced-fuzzy support vector machine (NA-FSVM) began as a usage of Structural Risk Minimization standard to create parallel classifications. Novel advanced-fuzzy support vector machine (NA-FSVM) rose up out of research in statistical learning hypothesis on the best way to manage speculation, and locate an ideal exchange off between structural many-sided quality and observational risk. Novel advanced-fuzzy support vector machine (NA-FSVM) classify points by assigning them to one of two disjoint half spaces, either in the example space or in a higher-dimensional element space.

Investigational outcomes

The four parameter combinations and corresponding forecast accuracies are given in Table 1, 2, 3 and 4. Four parameter combinations given in each of the four tables are assumed to be the best ones in representing all cases in the whole information set. With these parameter combinations, authors are presently ready to perform comparison experiments of the Novel advanced-fuzzy support vector machine (NA-FSVM). The information sets summarized in the tables 3 were connected to the Novel advanced-fuzzy support vector machine (NA-FSVM) with four diverse parameter combinations. Combinations are around the same. Nonetheless, since its normal holdout execution is generally more prominent than the others, the execution of the third parameter is moderately superior to others. Along these lines, the forecast execution of this parameter mix can be received as the best of the Fuzzy support vector machine show. For the selected parameter mix, the best holdout execution (88) was gotten in 2013 while the worst one was acquired in 1957. The forecast execution of spiral basis Novel advanced-fuzzy support vector machine (NA-FSVM) model is diverse for four parameter combinations and is less than that of the Fuzzy support vector machine demonstrate. The results showed that the Novel advanced-fuzzy support vector machine (NA-FSVM) gives a superior forecast execution than the fuzzy support vector machine display.

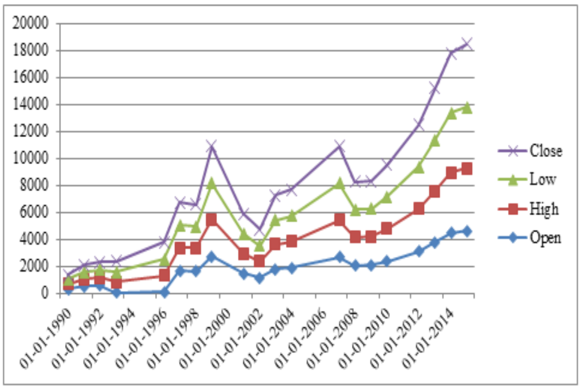

Figure 2. (left) Graphical representation showing the cases in NASDAQ Stock Market for every 1st October of every year

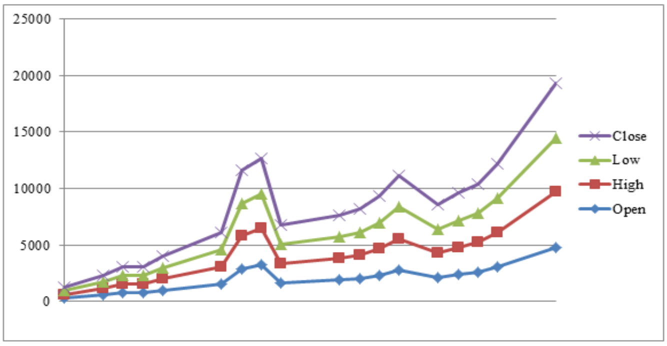

Figure 3. (right) Graphical representation showing the cases in NASDAQ Stock Market for every 12th October of every year

Conclusion

Foreseeing the bearing of movements of the stock market list is essential for the advancement of powerful market exchanging strategies. It usually affects a money related broker's decision to purchase or sell an instrument. Successful forecast of stock prices may promise alluring benefits for investors. These tasks are profoundly entangled and exceptionally troublesome. This study endeavored to anticipate the bearing of stock value development in the NASDAQ Stock Market, Standard and Poor's (S&P) Stock market.

Two expectation models of NASDAQ Stock Market, Standard and Poor's (S&P) Stock market were constructed and their performances were thought about on the day by day information from 1950 to 2015. Based on the test results got, some vital conclusions can be drawn. First of all, it should be emphasized that both the Fuzzy-support vector machine and NA-FSVM models showed significant execution in foreseeing the heading of stock value development. Thus, we can say that both the NA-FSVM is useful forecast tools for this point. The normal forecast execution of the NA-FSVM demonstrates 82.3% was discovered significantly superior to anything that of the Fuzzy-support vector machine show 79. 3%. To the best information of the authors, the expectation execution of the proposed models outperforms similar studies in the writing. Notwithstanding, forecast performances of our models might be enhanced by two ways. The first is to adjust the model parameters by leading a more sensitive and comprehensive parameter setting, which can be a future work for interested

The principal feature is to regulate the classic parameters by leading a more sensitive and comprehensive parameter setting, which can be a future work for interested readers. Second, extraordinary or extra info variables can be used in the models. In spite of the fact that we received ten specialized indicators, some other large scale financial variables such as outside trade rates, interest rates and consumer value record and so on can be used as inputs of the models. Nevertheless, ten specialized indicators received here demonstrated that they are useful in anticipating the course of stock value development. Another imperative issue that should be specified here is the differences among the expectation performances for every year. Under such circumstances of crisis, a decrease in the expectation execution of specialized indicators can be considered worthy.

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