Available Online at www.ijecse.org ISSN- 2277-1956

Predicting future trends in stock market by decision tree rough-set based hybrid system with HHMM

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Abstract- **Around the world, trading in the stock market has gained huge attractiveness as a means through which, one can obtain vast profits. Attempting to profitably and precisely predict the financial market has long engrossed the interests and attention of bankers, economists and scientists alike. Stock market prediction is the act of trying, to determine the future value of a company's stock or other financial instrument traded on a financial exchange. Accurate stock market predictions are important for many reasons. Chief among all is the need for investors, to hedge against potential market risks and the opportunities for arbitrators and speculators, to make profits by trading indexes. Stock Market is a place, where shares are issued and traded. These shares are either traded through Stock exchanges or Over-the-Counter in physical or electronic form. Data mining, as a process of discovering useful patterns, correlations has its own role in financial modeling. Data mining is a discipline in computational intelligence that deals with knowledge discovery, data analysis and full and semi-autonomous decision making. Prediction of stock market by data mining techniques has been receiving a lot of attention recently. This paper presents a hybrid system based on decision tree-rough set, for predicting the trends in the Bombay Stock Exchange (BSESENSEX) with the combination of Hierarchical Hidden Markov Model. In this paper we present future trends on the bases of price earnings and dividend. The data on accounting earnings when averaged over many years help to predict the present value of future dividends.**

Keywords: Stock market, Data mining, CART, Rough set, HHMM, technical indicator.

I. INTRODUCTION

In finance stock market returns forecasting is an important issue. However, information concerning a stock is normally vague, uncertain and incomplete making it a dare to predict the future economic performance. Accurate stock market predictions are important for many reasons. Chief among all is the need for investors, to hedge against potential market risks and the opportunities for arbitrators and speculators, to make profits by trading indexes. Traditional analysis methods reliability is strongly relying on experience, is somewhat being doubted due to the complication of correlated information, and the mode of stock exchange. The successful prediction, of a stock's future price could yield considerable profit. However, according to the efficient market hypothesis, all such attempts at prediction are futile, as all the information that could affect the activities of stock price or the market index must have been already incorporated, into the current market quotation. A majorly used forecasting method in financial area is either technical or fundamental. Technical Analysis provides an outline for studying investor behavior, and generally focuses only on price and volume data. Data mining, as a process of discovering useful patterns, correlations has its own role in financial modeling. It entails the analysis of data sets, such that unsuspected relationships among data objects are found. Data analysis task is classification, where a model or classifier is constructed to predict categorical labels. Classification can be defined as a development in which specified set of data records are separated into training and test data sets. For validating the model we required the test data record and for constructing the classification model training data set is required. The constructed classification model is used for classifying and predicting new data set records. In this paper we proposed a hybrid system by using classification methods and HHMM which describes the future market trends based on historical stock market data.

The reminder of this paper is organized as follows: in Section 2, we briefly provides a survey of forecasting techniques; in Section 3 there is a description of proposed system; Section 4 describes about various algorithms and methods used in this system; Section 5 to the discussion of experimental results; Section 6 conclusions.

II. LITERATURE SURVEY

Data mining techniques and artificial neural networks have been widely used prediction of financial time series. In [1] Technical indicators and rough-set based system were used to predict on-day-ahead trend of SENSEX. In [2], technical indicators and a backpropagation neural network were used to create a decision support system for exchange traded funds trading. Technical indicators and neural networks were used in [3] to predict the US Dollar Vs British Pound exchange ratesIn [4], review of data mining applications in stock markets was presented. [5] Used a two-layer bias decision tree with technical indicators feature to create a decision rule that can make recommendations when to buy a stock and when not to buy it. [6] Combined the filter rule and the decision tree technique for stock trading. In [7] a hybrid fuzzy time series model with cumulative probability distribution approach and rough set rule induction was proposed, to forecast stock markets. Cumulative probability distribution approach was used to discretize the observations in training datasets based on the characteristics of data distribution and rules were generated using rough set algorithm. Forecasting was then done based on rule support values from rough set algorithm.

III. PROPOSED SYSTEM

The trend prediction system proposed in this paper works in the following way: First the features are extracted from the daily stock market data. Then the relevant features are selected using decision tree. A rough set based classifier is then used to predict the next day's trend using the selected features. Then these trends are evaluated using HHMM and final predictions will generate. In the present study, the prediction accuracy of the proposed system is validated using the Bombay Stock Exchange Sensitive Index (BSE-SENSEX or commonly, SENSEX) data. The performance of trend prediction systems are evaluated using the cross validation method.

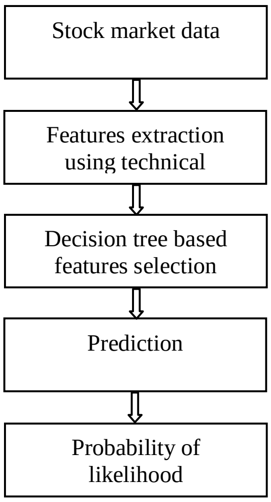

Fig 1Proposed system

Stock market data: In the proposed trend prediction system, data from stock market is considered for the study. Four datasets are considered for the study.

a. A SENSEX data from 1960 to 2011 is considered for the purpose.

b. SENSEX data from Reliance Company is also considered for testing the proposed system.

c. Another company TATA is considered for study.

d. And at last dataset of Maruti is considered.

All the datasets are tested against proposed system and make predictions in the last step of the system.

Feature extraction: In the proposed system, we perform technical analysis for prediction. Features are extracted from the stock market data. From all the above listed companies, data are selected, now some features are extracted like price, earning etc. from the database. Different features are selected for each dataset.

Feature selection: Features which are extracted in previous step is now processed with decision tree algorithm and according to the algorithm relevant features are selected for the purpose of prediction. Here in proposed system CART decision tree algorithm is used for tree creation. Tree is a flow chart like structure where each internal node represents a test on an attribute and leave node holds a class label. During tree construction attribute selection measures are use for selecting, the attribute which provide best partitioning of tuples into distinct classes. CART uses GINI index as an attribute selection measure. When decision tree is created many of the branches reflect outlier or noise in the training set by tree pruning, such classes are identified and removed with the goal of improving classification accuracy on unseen data [15, 13].

Prediction: In this step rough set is used for predicting the future trends in stock market. As we mentioned in previous chapter rough set is capable in dealing with imperfect knowledge. After tree creation attributes are split according to the decision rule. Mathematical rough set is then applied on the attributes and the prediction will generate. A rough set based classifier is used to predict the next day's trend using the selected features. Here in proposed system rough set uses t- distribution for the calculations of future values of stock [8, 11].

Probability of likelihood: In this last step of proposed system, the values come from the previous step is evaluated by HHMM and the final future prediction will generate. It will also calculate the probability of likelihood. So that the person who wants to know about the stock's value. So that the person will easily find out the correct time to invest in stocks. hierarchical hidden Markov model (HHMM) which describes the market trend in terms of states whose transition/permanence probabilities depends on past states and underlying price dynamics, within a given time window [10].

IV. ALGORITHM & METHODS

1. Select stream data from BSESENSEX database.
2. Extract features from the stock dataset using technical indicators.
3. Features are selected using CART decision tree
    a. Calculate the impurity function.
    b. Partitioning is based upon impurity function.
    c. Generate tree according to splitting criteria.
    d. Tree pruning.
4. Apply rough set on trained data
    a. Calculate number of items.
    b. Apply cross validation.
    c. Calculation for regression.
    d. Find statistic values.
    e. Apply correlation
    f. Calculation for t-test
5. Prediction is generated.
6. Apply HHMM on the predicted values which are generated by above steps
    a. Find transition matrix.
    b. Generate test sequence.
    c. Calculate probability.
7. Final results.

A. CART

The CART decision tree is a binary recursive partitioning procedure capable of processing continuous and nominal attributes both as targets and predictors. Data are handled in their raw form; no binning is required or recommended. Trees are grown to a maximal size without the use of a stopping rule and then pruned back (essentially split by split) to the root via cost-complexity pruning [13].

CART splitting rules

An instance goes left if CONDITION, and goes right otherwise,

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where the CONDITION is expressed as "attribute *Xi* <= *C*" for continuous attributes. For nominal attributes the CONDITION is expressed as membership in an explicit list of values [17].

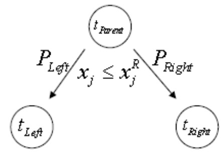

Fig 2 Decision tree rules

Attribute selection measure:

Splitting in regression trees is made in accordance with squared residuals minimization algorithm which implies that expected sum variances for two resulting nodes should be minimized.

$$\underset{x_j \le x_j^R,\ j=1,\ldots,M}{\arg\min} \left[P_l Var(Y_l) + P_r Var(Y_r) \right]$$

where Var(Yl),Var(Yr) - reponse vectors for corresponding left and right child nodes, xj _ x^R_j , j = 1, . . . ,M - optimal splitting question which satisfies the above condition. Squared residuals minimization algorithm is identical to Gini splitting rule. If we assign to objects of class k the value 1, and value 0 to objects of other classes, then sample variance of these values would be equal to p(k|t)[1 − p(k|t)]. Summarizing by number of classes K, we will get the following impurity measure i(t):

$$i(t) = 1 - \sum_{k=1}^{K} p^2(k \mid t)$$

Up to this point maximum tree was constructed which means that splitting was made up to the last observations in learning sample. Maximum tree may turn out to `be very big, especially in the case of regression trees, when each response value may result in a separate node [12].

B. Rough set

In the proposed system, mathematical rough set is applied to calculate future values of stock. Method is worked as follows:

- Firstly calculate number of items preset in the dataset.
- *Cross validation*

It is sometimes called rotation estimation. It is a technique for assessing how the results of a statistical analysis will generalize to an independent data set. "Cross-validation is a method to predict the fit of a model to a hypothetical validation set when an explicit validation set is not available".

- *k-fold cross-validation*

In *k*-fold cross-validation the original sample is randomly partitioned into *k* subsamples. Of the *k* subsamples, a single subsample is retained as the validation data for testing the model, and the remaining *k* − 1subsamples are used as training data. The cross-validation process is then repeated *k* times (the *folds*), with each of the *k* subsamples used exactly once as the validation data. The *k* results from the folds then can be averaged, to produce a single estimation. In proposed system 10-fold cross validation method is used.

- *Regression calculation:*

Regression analysis can be used to model the relationship between one or more independent or predictor variables and a dependent or response variable (which continuous-valued). Let D be a training set consisting values of predictor variables, set contain D data points of the form (x1,y1), (x2,y2), …., ($x_{|D|}$,$y_{|D|}$). The regression coefficient can be estimated by the following equation [8, 11]:

$$w_1 = \frac{\sum_{i=1}^{|D|} \left(xi - \overline{x}\right)\left(yi - \overline{y}\right)}{\sum_{i=1}^{|D|} \left(xi - \overline{x}\right)^2}$$

- *Statistic values:* Here we use earning values present in stock dataset as a statistic values.
- *Average:* Calculate average of regression values and statistic values using following formula [14]:

$$A_n = \frac{\sum_{i=1}^{n} v_i}{n}$$

where n is number of elements, i=1,2,3, …, n, and v is either regression value or statistic value.

- *Correlation:* It is calculated using following formula [32]:

$$r_{xy} = \frac{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)\left(yi - \bar{y}\right)}{(n-1)s_x s_y} = \frac{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2 \sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}}$$

where x and y are the sample means of *X* and *Y*, and s_x and s_y are the sample standard deviations of *X* and *Y*.

- *t-Test:*

The t-value for feature 'a' (price, dividend, earning,) is expressed by:

$$t(a) = \frac{\mu_1 - \mu_2}{\sqrt{\sigma_1^2 / n_1 + \sigma_2^2 / n_2}}$$

Where μ_i & σ_i are the mean and the standard deviation of the expression level of feature 'a' for i=1, 2, …, n when there are multiple classes of samples, the t-value is typically computed for one class versus all the other classes. The top feature ranked by t-value can be selected for data mining. Feature selection based on rough set theory is used to minimize the feature set [8, 11].

- Algorithm :
  1. Calculate t-value of each feature, select to ranked n features to form the feature set C.
  2. Discretize the feature set C.
  3. Set P=C
  4. do
  5. for each a∈P
  6. if $\gamma_{p-\{a\}}(D)==\gamma_c(D)$
  7. P=P-{a}
  8. Until $\gamma_{(P-\{a\})}(D)<\gamma_{(C)}(D)$
  9. Return P. [8]

C. HHMM

HHMMs are structured multi-level stochastic processes. They generalize ordinary HMM by making states probabilistic models on their own. Therefore, HHMMs are recursively defined, so that each state at level l relies on an HHMM of layer l+1. When a state in an HHMM is activated, it becomes active also its own probabilistic model and one of the states of the underlying HHMM is activated recursively. This process is repeated until a *production state*, which is a state that emits a single observation symbol, is activated. The states that do not directly emit observations symbols are called *internal states*. Production states do not hold a sub-model, and they are not able to transit to other states. So, when the production state is reached, a symbol of sequence is produced, the control goes back to the calling state, that in turn gives the control to another state at the same level. When a *terminal state* is reached, the control is moved to the upper level [9, 10].

In fig 4.3 states are represented by circles, and transitions between states by arrows. In particular, black solid lines show intra-level transitions. Transitions from upper to lower level are denoted by fine-dashed lines. Transitions back to upper levels are denoted by dashed lines. Bold circles are the production states, which are the solely allowed to produce a symbol $\sigma_k \in \Sigma$, Σ is the alphabet of emitted symbols, observed in sequences. Gray circles are terminal. The other circles are internal.

Formally an HHMM is defined as a pair <G, λ>, where G is D-layer directed graph, and $\lambda \equiv \{\lambda_d\}_{d=1..D}$ a collection of parameter, specific of each layer d. The graph G is made of inner, production and terminal states. An inner state at level d of an HHMM is denoted by q_d, while q^d_E is the terminal state and we collect the inner states and the production state at level d in $Q_d \equiv \{q_i^d, q_E^d\}$ [5]. It is not required an internal state to have the same number of substates, although any HHMM can be transformed into a model with an equal number of sub-states for each internal

probability of moving o^d_k is a production state emitting the symbol $\sigma_k \in \Sigma$. from i-th to j-th sub-state of q^d. Similarly, $\pi_i^{q^d} = \Pr(q_i^{d+1} \mid q_d)$ is the initial probability assigned to sub-states by q^d. It can be regarded as the probability of performing a vertical transition, that is the probability by which the state q^d activates the sub state q_i^{d+1} . We denote the activation probability distribution by $\pi^{q^d} = \{\pi_i^{q^d}\}$ .Finally, $B^{q^d} = \{b^{q^d}(o_k)\}$ is the probability that internal state q will

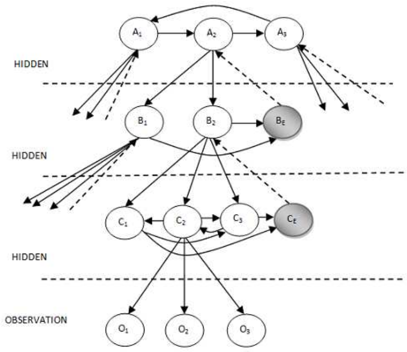

Fig 3 Three layers HHMM

activate the production state o_k^{d+1} , which in turn will emit the symbol σ_k. Therefore $b^{q^d}(o_k)$ is also the probability that the symbol $\sigma_k \in \Sigma$ is produced when the state q_d is activated. In summary, we get $\lambda_d = \{A^{q^d}, \pi^{q^d}, B^{q_E^d}\}_{q^d, q_E^d \in Q_d}$. States and observations can be either discrete or continuous [9, 10].

V. RESULTS

Input: BSESENSEX data is taken for the study. Data set contains five attributes, namely serial number (sno), year, price (sp), earning and dividend. Three features earning. Price and dividend is use for prediction process. Dataset contains values from year 1960 to 2011. Dataset contains 52 instances.

	Transactions				
1	sno	Year	sp	earning	Dividend
2	1	1960	58.1100	3.1000	1.9800
3	10	1969	92.0600	6.1000	3.2400
4	11	1970	92.1500	5.5100	3.1900
5	12	1971	102.0900	5.5700	3.1600
6	13	1972	118.0500	6.1700	3.1900
7	14	1973	97.5500	7.9600	3.6100
8	15	1974	68.5600	9.3500	3.7200
9	16	1975	90.1900	7.7100	3.7300
10	17	1976	107.4600	9.7500	4.2200
11	18	1977	95.1000	10.8700	4.8600
12	19	1978	96.1100	11.6400	5.1800
13	2	1961	71.5500	3.3700	2.0400
14	20	1979	107.9400	14.5500	5.9700
15	21	1980	135.7600	14.9900	6.4400
16	22	1981	122.5500	15.1800	6.8300
17	23	1982	140.6400	13.8200	6.9300
18	24	1983	164.9300	13.2900	7.1200
19	25	1984	167.2400	16.8400	7.8300
20	26	1985	211.2800	15.6800	8.2000

Fig 4 Dataset of stock market

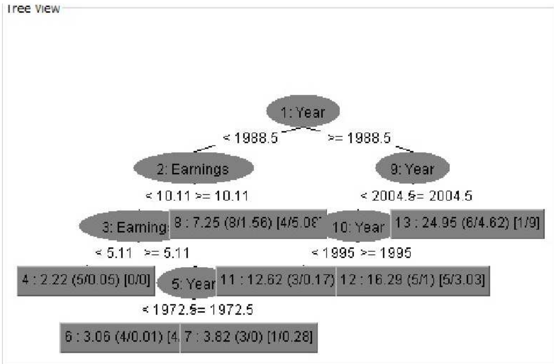

Fig 5 Decision Tree

	Transactions						
38	37	1996	740.7400	40.6300	14.8900	NaN	
39	38	1997	970.4300	44.0900	15.5200	NaN	
40	39	1998	1.2292e+03	44.2700	16.2000	NaN	
41	40	1999	1.4693e+03	51.6800	16.7100	NaN	
42	41	2000	1.3203e+03	56.1300	16.2700	NaN	
43	42	2001	1.1481e+03	38.8500	15.7400	NaN	
44	43	2002	879.8200	46.0400	16.0800	NaN	
45	44	2003	1.1119e+03	54.6900	17.8800	NaN	
46	45	2004	1.2119e+03	67.6800	19.4070	NaN	
47	46	2005	1.2483e+03	76.4500	22.3800	NaN	
48	47	2006	1.4183e+03	87.7200	25.0500	NaN	
49	48	2007	1.4684e+03	82.5400	27.7300	NaN	
50	49	2008	903.2500	65.3900	28.0500	NaN	
51	50	2009	1.1151e+03	59.6500	22.3100	NaN	
52	51	2010	1.2576e+03	83.6600	23.1200	NaN	
53	52	2011	1.2576e+03	97.0500	26.0200	NaN	
54	NaN	N	54	54	54	NaN	
55	NaN	AVG	487.1256	28.5755	11.4169	NaN	
56	NaN	STDEV	491.5498	26.0940	7.6680	NaN	

Fig 6 Output after CART and rough set implementation

Results of HHMM

The dataset, having 4 attribute sides, labeled 1 through 4.
A weighted sp is, for which the probability of heads is 0.11 and the probability of occurrence is 0.89
A weighted earning, for which the probability of heads is 0.28 and the probability of tails is 0.72.
Transition matrix

$$\begin{bmatrix} 0.11 & 0.89 \\ 0.28 & 0.72 \end{bmatrix}$$

Generate a test sequence
The following commands create the transition and emission matrices for the model

$$TRANS = \begin{bmatrix} 0.11 & 0.28 & 0.89 & 0.72 \end{bmatrix}$$

$$EMIS = \begin{bmatrix} 1/4 & 1/4 & 1/4 & 1/4 & 1/4 & 1/4 \\ 5/8 & 1/8 & 1/8 & 1/8 & 1/8 & 1/8 \end{bmatrix}$$

To generate a random sequence of states and emission from the model
[seq, states]=hmmgenerate(1000, TRANS, EMIS);
Likely states
TRANS=[.9 .1; 5 .95];
EMIS=[1/4, 1/4 ,1/4, 1/4;…. 5/8, 1/8, 1/8, 1/8];
[seq, states]=hmmgenerate(1000, TRANS, EMIS);
Likelystates=hmmviterbi(seq, TRANS, EMIS);
Sum(states==likelystates)/1000
Result = 0.7380 (probability of likelihood)

ISSN 2277-1956/V1N3-1578-1587

We can compare the outputs with the original transitional and emission matrices, TRANS and EMIS:
[TRANS_EST, EMIS_EST]=hmmestimates(seq, states)

TRANS_EST= 0.9079 0.0921
0.0409 0.9591

EMIS_EST= 0.2508 0.2286 0.2730 0.2476
0.4000 0.4277 0.0861 0.0861

TRANS= 0.9000 0.1000
0.0500 0.9500

EMIS= 0.2500 0.2500 0.2500 0.2500
0.6250 0.6250 0.1250 0.1250

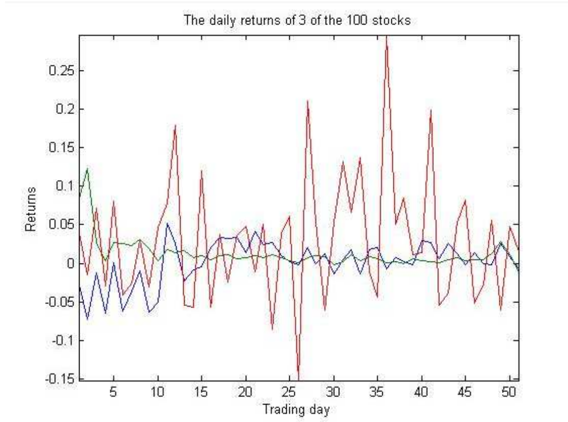

Fig 7 shows the predicted variations in price, earning and dividend

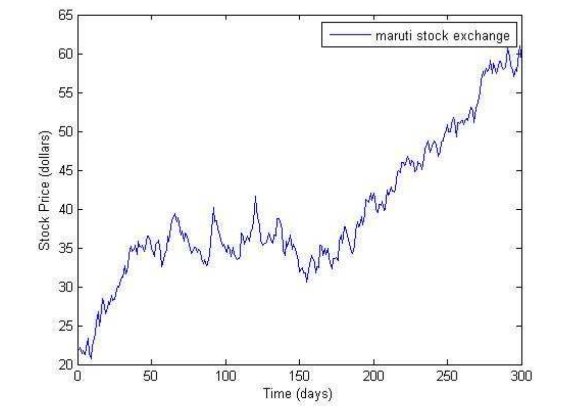

Fig 8 shows the graph of maruti dataset

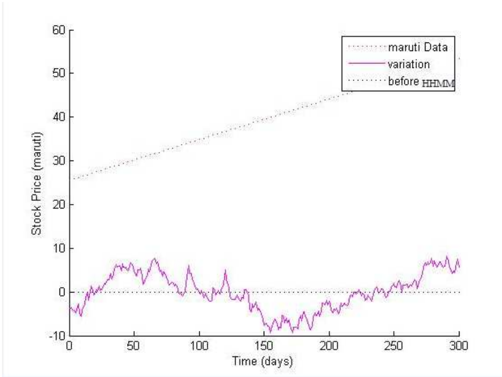

Fig 9 shows the variations in dataset after applying rough set and HHMM

VI. CONCLUSION

Predicting the future is one aspect in designing profitable day trading strategies. Technical analysis analyzes price, volume and other market information, whereas fundamental analysis looks at the facts of the company, market, currency or commodity. Most large brokerage, trading group, or financial institutions will typically have both a technical analysis and fundamental analysis team. Here in this paper technical analysis is considered for the study. The design of decision tree-rough set based stock market trend prediction system with the combination of HHMM for predicting the future trend of the SENSEX is presented in this paper. Features are extracted from the historical SENSEX data by using CART. Extracted features are used to generate the prediction rules using rough set theory because rough sets are extremely useful in dealing with incomplete or imperfect knowledge. HHMMs are useful in applications dealing with sequences of symbols. It is observed by study that the hybrid rough set based system is more accurate then stands alone rough set based system. Whereas when we combined hybrid system with HHMM then it gives much better results. It is observed that the hybrid decision tree-rough set based trend prediction system produces an accuracy of 90.22%. The stand-alone rough set based trend prediction system, without any feature selection, produced an accuracy of 88.18 %. Whereas a proposed trend prediction system with HHMM produces an accuracy of 92.1%. It can be concluded from the present study that decision tree-rough set based hybrid trend prediction system with HHMM is well suited for stock market trend prediction.

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