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RESEARCH

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DeConFuse: a deep convolutional transform-based unsupervised fusion framework

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Abstract

This work proposes an unsupervised fusion framework based on deep convolutional transform learning. The great learning ability of convolutional filters for data analysis is well acknowledged. The success of convolutive features owes to the convolutional neural network (CNN). However, CNN cannot perform learning tasks in an unsupervised fashion. In a recent work, we show that such shortcoming can be addressed by adopting a convolutional transform learning (CTL) approach, where convolutional filters are learnt in an unsupervised fashion. The present paper aims at (i) proposing a deep version of CTL, (ii) proposing an unsupervised fusion formulation taking advantage of the proposed deep CTL representation, and (iii) developing a mathematically sounded optimization strategy for performing the learning task. We apply the proposed technique, named DeConFuse, on the problem of stock forecasting and trading. A comparison with state-of-the-art methods (based on CNN and long short-term memory network) shows the superiority of our method for performing a reliable feature extraction.

Keywords: Information fusion, Deep learning, Convolution, Stock trading, Financial forecasting

1 Introduction

In the last decade, convolutional neural network (CNN) has enjoyed tremendous success in different types of data analysis. It was initially applied for images in computer vision tasks. The operations within the CNN were believed to mimic the human visual system. Although such a link between human vision and CNN may be present, it has been observed that deep CNNs are not exact models for human vision [1]. For instance, biologists consider that the human visual system would consist of 6 layers [2, 3] and not 20+ layers used in GoogleNet [4].

Neural network models have also been used for analyzing time series data. Until recently, long short-term memory (LSTM) networks were the almost exclusively used neural network models for time series analysis as they were supposed to mimic memory and hence were deemed suitable for such tasks. However, LSTM are not able to model

very long sequences, and their training is hardware intensive. Owing to these shortcomings, LSTMs are being replaced by CNNs. The reason for the great results of CNN methods for time series analysis (1D data processing in general) is not well understood. One possibility may lie in the universal function approximation capacity of deep neural networks [5, 6] rather than its biological semblance. The research in this area is primarily led by its success rather than its understanding.

An important point to mention is that the performance of CNN is largely driven by the availability of very large labeled datasets. This probably explains their tremendous success in facial recognition tasks. Google's FaceNet [7] and Facebook's DeepFace [8] architectures are trained on 400 million facial images, a significant proportion of world's population. These companies are easily equipped with gigantic labeled facial images data as these are "tagged" by their respective users. In the said problem, deep networks reach almost 100% accuracy, even surpassing human capabilities. However, when it comes to tasks that require expert labeling, such as facial recognition from sketches (requiring forensic expertise) [8] or ischemic attack detection from EEG (requiring medical expertise) [9], the accuracies become modest. Indeed, such tasks require expert labeling that is difficult to acquire, thus limiting the size of available labeled dataset.

The same is believed by a number of machine learning researchers, including Hinton himself, who are wary of supervised learning. In an interview with Axios¹, Hinton mentioned his "deep suspicion" on backpropagation, the workhorse behind all supervised deep neural networks. He even added that "I don't think it's how the brain works," and "We clearly don't need all the labeled data." It seems that Hinton is hinting towards unsupervised learning frameworks. Unsupervised learning technique does not require targets/labels to learn from data. This approach typically takes benefit from the fact that data is inherently very rich in its structure, unlike targets that are sparse in nature. Thus, it does not take into account the task to be performed while learning about the data, saving from the need of human expertise that is required in supervised learning. More on the topic of unsupervised versus supervised learning can be found in a blog by DeepMind².

In this work, we would like to keep the best of both worlds, i.e., the success of convolutional models from CNN and the promises of unsupervised learning formulations. With this goal in mind, we developed convolutional transform learning (CTL) [10]. This is a representation learning technique that learns a set of convolutional filters from the data without label information. Instead of learning the filters (by backpropagating) from data labels, CTL learns them by minimizing a data fidelity loss, thus making the technique unsupervised. CTL has been shown to outperform several supervised and unsupervised learning schemes in the context of image classification. In the present work, we propose to extend the shallow CTL version to deeper layers, with the aim to generate a feature extraction strategy that is well suited for 1D time series analysis. This is the first major contribution of this work—deep convolutional transform learning.

In most applications, time series signals are multivariate, as they arise from multiple sources/sensors. For example, biomedical signals like ECG and EEG come from multiple leads; financial data from stocks are recorded with different inputs (open, close, low, high, and net asset value) and demand forecasting problems in smartgrids come with multiple

¹<https://www.axios.com/artificial-intelligence-pioneer-says-we-need-to-start-over-1513305524-f619efbd-9db0-4947-a9b2-7a4c310a28fe.html>

²<https://deepmind.com/blog/article/unsupervised-learning>

types of data (power consumption, temperature, humidity, occupancy, etc.). In all such cases, the final goal is to perform prediction/classification task from such multivariate time series. We propose to address such problem as one of feature fusion. The information from each of the sources will be processed by the proposed deep CTL pipeline, and the generated deep features will be finally fused by an unsupervised fully connected layer. This is the second major contribution of this work—an unsupervised fusion framework with deep CTL.

The resulting features can be used for different applicative tasks. In this paper, we will focus on the applicative problem of financial stock analysis. The ultimate goal may be either to forecast the stock price (regression problem) or to decide whether to buy or sell (classification problem). Depending on the considered task, we can pass the generated features into suitable machine learning tool that may not be as data hungry as deep neural networks. Therefore, by adopting such a processing architecture, we expect to yield better results than traditional deep learning especially in cases where access to labeled data is limited.

2 Literature review

2.1 CNN for time series analysis

Let us briefly review and discuss CNN-based methods for time series analysis. For a more detailed review, the interested reader can peruse [11]. We mainly focus on studies on stock forecasting as it will be our use case for experimental validation.

The traditional choice for processing time series with neural network is to adopt a recurrent neural network (RNN) architecture. Variants of RNN like long short-term memory (LSTM) [12] and gated recurrent unit (GRU) [13] have been proposed. However, due to the complexity of training such networks via backpropagation through time, they have been progressively replaced with 1D CNN [14]. For example, in [15], a generic time series analysis framework was built based on LSTM, with assessed performance on the UCR time series classification datasets https://www.cs.ucr.edu/~eamonn/time_series_data/. The later study from the same group [17], based on 1D CNN, showed considerable improvement over the prior model on the same datasets.

There are also several studies that convert 1D time series data into a matrix form so as to be able to use 2D CNNs [16, 18, 19]. Each column of the matrix corresponds to a subset of the 1D series within a given time window, and the resulting matrix is processed as an image. The 2D CNN model has been especially popular in stock forecasting. In [19], the said techniques have been used on stock prices for forecasting. A slightly different input is used in [20]: instead of using the standard stock variables (open, close, high, low, and NAV), it uses high frequency data for forecasting major points of inflection in the financial market. In another work [21], a similar approach is used for modeling exchange -traded fund (ETF). It has been seen that the 2D CNN model performs the same as LSTM or the standard multi-layer perceptron [22, 23]. The apparent lack of performance improvement in the aforementioned studies may be due to an incorrect choice of CNN model, since an inherently 1D time series is modeled as an image.

2.2 Deep learning and fusion

We now review existing works for processing multivariate data inputs, within the deep

learning framework. Since the present work aims at being applied to stock price forecasting/trading, we will mostly focus our review on the multi-channel/multi-sensor fusion framework. Multimodal data and fusion for image processing, less related to our work, will be mentioned at the end of this subsection for the sake of completeness.

Deep learning has been widely used recently for analyzing multi-channel/multi-sensor signals. In several of such studies, all the sensors are stacked one after the other to form a matrix and 2D CNN is used for analyzing these signals. For example, [24] uses this strategy for analyzing human activity recognition from multiple body sensors. It is important to distinguish such an approach from the aforementioned studies [19–23]. Here, the images are not formed from stacking windowed signals from the same signal one after the other, but by stacking signals from different sensors. The said study [24] does not account for any temporal modeling; this is rectified in [25]. In there, 2D CNN is used on a time series window; but the different windows are finally processed by GRU, thus explicitly incorporating time series modeling. There is however no explicit fusion framework in [24, 25]. The information from raw multivariate signals is simply fused to form matrices and treated by 2D convolutions. A true fusion framework was proposed in [26]. Each signal channel is processed by a deep 1D CNN, and the output from the different signal processing pipelines are then fused by a fully connected layer. Thus, the fusion is happening at the feature level and not in the raw signal level as it was in [24, 25].

Another area that routinely uses deep learning based fusion is multi-modal data processing. This area is not as well defined as multi-channel data processing; nevertheless, we will briefly discuss some studies on this topic. In [27], a fusion scheme is shown for audio-visual analysis that uses a fusion scheme for deep belief network (DBN) and stacked autoencoder (SAE) for fusing audio and video channels. Each channel is processed separately and connected by a fully connected layer to produce fused features. These fused features are further processed for inference. We can also mention the work on video-based action recognition addressed in [28], which proposes a fusion scheme for incorporating temporal information (processed by CNN) and spatial information (also processed by CNN).

There are several other such works on image analysis [29–31]. In [29], a fusion scheme is proposed for processing color and depth information (via 3D and 2D convolutions, respectively) with the objective of action recognition. In [30], it was shown that by fusing hyperspectral data (high spatial resolution) with Lidar (depth information), better classification results can be achieved. In [31], it was shown that fusing deeply learnt features (from CNN) with handcrafted features via a fully connected layer can improve analysis tasks. In this work, our interest lies in the first problem; that of inference from 1D/time-series multi-channel signals. To the best of our knowledge, all prior deep learning-based studies on this topic are supervised. In keeping with the vision of Hinton and others, our goal is to develop an unsupervised fusion framework using deeply learnt convolutive filters.

2.3 Convolutional transform learning

Convolutional transform learning (CTL) has been introduced in our seminal paper [10]. Since it is a recent work, we present it in detail in the current paper, to make it self-content. CTL learns a set of filters $(t_m)_{1 \leq m \leq M}$ operated on observed samples $(s^{(k)})_{1 \leq k \leq K}$

to generate a set of features $(x_m^{(k)})_{1 \leq m \leq M, 1 \leq k \leq K}$. Formally, the inherent learning model is expressed through convolution operations defined as

$$(\forall m \in \{1, \dots, M\}, \forall k \in \{1, \dots, K\}) \quad t_m * s^{(k)} = x_m^{(k)}. \quad (1)$$

Following the original study on transform learning [32], a sparsity penalty is imposed on the features for improving representation ability and limit overfitting issues. Moreover, in the same line as CNN models, the non-negativity constraint is imposed on the features. Training then consists of learning the convolutional filters and the representation coefficients from the data. This is expressed as the following optimization problem

$$\begin{aligned} \underset{(t_m)_{m=1}^M, (x_m^{(k)})_{m,k}}{\text{minimize}} \quad & \frac{1}{2} \sum_{k=1}^K \sum_{m=1}^M \left(\|t_m * s^{(k)} - x_m^{(k)}\|_2^2 + \psi(x_m^{(k)}) \right) \\ & + \mu \sum_{m=1}^M \|t_m\|_2^2 - \lambda \log \det([t_1 | \dots | t_M]), \end{aligned} \quad (2)$$

where ψ is a suitable penalization function. Note that the regularization term “ $\mu \|\cdot\|_F^2 - \lambda \log \det$ ” ensures that the learnt filters are unique, something that is not guaranteed in CNN. Let us introduce the matrix notation

$$T * S - X = \begin{bmatrix} t_1 * s^{(1)} - x_1^{(1)} & \dots & t_M * s^{(1)} - x_M^{(1)} \\ \vdots & \ddots & \vdots \\ t_1 * s^{(K)} - x_1^{(K)} & \dots & t_M * s^{(K)} - x_M^{(K)} \end{bmatrix} \quad (3)$$

where $T = [t_1 \dots t_M]$, $S = [s^{(1)} \dots s^{(K)}]^\top$, and $X = [x_1^{(k)} \dots x_M^{(k)}]_{1 \leq k \leq K}$. The cost function in problem (2) can be compactly rewritten as³

$$F(T, X) = \frac{1}{2} \|T * S - X\|_F^2 + \Psi(X) + \mu \|T\|_F^2 - \lambda \log \det(T), \quad (4)$$

where Ψ applies the penalty term ψ column-wise on X .

A local minimizer to (4) can be reached efficiently using the alternating proximal algorithm [33–35], which alternates between proximal updates on variables T and X . More precisely, set a Hilbert space $(\mathcal{H}, \|\cdot\|)$ and define the proximity operator [23] at $\tilde{x} \in \mathcal{H}$ of a proper lower-semi-continuous convex function $\varphi : \mathcal{H} \rightarrow]-\infty, +\infty]$ as

$$\text{prox}_\varphi(\tilde{x}) = \arg \min_{x \in \mathcal{H}} \varphi(x) + \frac{1}{2} \|x - \tilde{x}\|^2. \quad (5)$$

Then, the alternating proximal algorithm reads

$$\begin{aligned} & \text{For } n = 0, 1, \dots \\ & \begin{cases} T^{[n+1]} = \text{prox}_{\gamma_1 F(\cdot, X^{[n]})}(T^{[n]}) \\ X^{[n+1]} = \text{prox}_{\gamma_2 F(T^{[n+1]}, \cdot)}(X^{[n]}) \end{cases} \end{aligned} \quad (6)$$

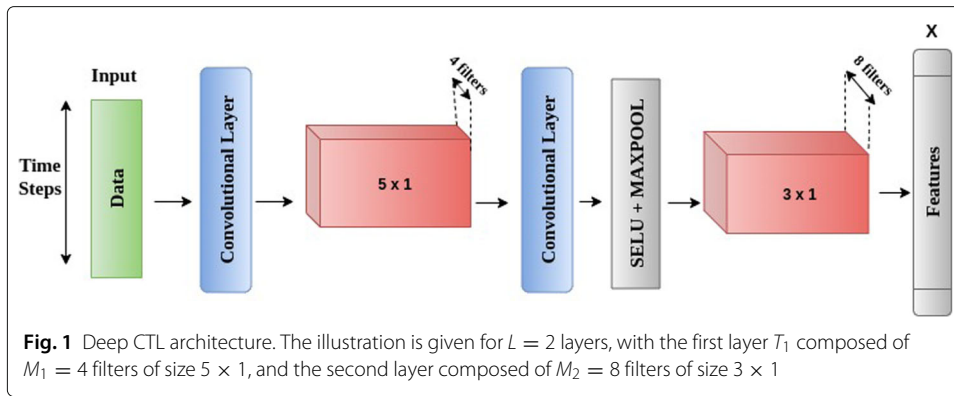
with initializations $T^{[0]}$, $X^{[0]}$ and γ_1, γ_2 positive constants. For more details on the derivations and the convergence guarantees, the readers can refer to [10].

3 Fusion based on deep convolutional transform learning

In this section, we discuss our proposed formulation. First, we extend the aforementioned CTL formulation to a deeper version. Next, we develop the fusion framework based on transform learning, leading to our DeConFuse⁴ strategy.

³Note that T is not necessarily a square matrix. By an abuse of notation, we define the “log-det” of a rectangular matrix as the sum of logarithms of its singular values.

⁴Code available at: <https://github.com/pooja290992/DeConFuse.git>



3.1 Deep convolutional transform learning

Deep CTL consists of stacking multiple convolutional layers on top of each other to generate the features, as shown in Fig. 1. To learn all the variables in an end-to-end fashion, deep CTL relies on the key property that the solution \hat{X} to the CTL problem, assuming fixed filters T , can be reformulated as the simple application of an element-wise activation function, that is

$$\operatorname{argmin}_X F(T, X) = \phi(T * S), \quad (7)$$

with ϕ the proximity operator of Ψ [36]. For example, if Ψ is the indicator function of the positive orthant, then ϕ identifies with the famous rectified linear unit (ReLU) activation function. Many other examples are provided in [36]. Consequently, deep features can be computed by stacking many such layers

$$(\forall \ell \in \{1, \dots, L-1\}) \quad X_\ell = \phi_\ell(T_\ell * X_{\ell-1}), \quad (8)$$

where $X_0 = S$ and ϕ_ℓ a given activation function for layer ℓ .

Putting all together, deep CTL amounts to

$$\underset{T_1, \dots, T_L, X}{\text{minimize}} \quad F_{\text{conv}}(T_1, \dots, T_L, X | S) \quad (9)$$

where

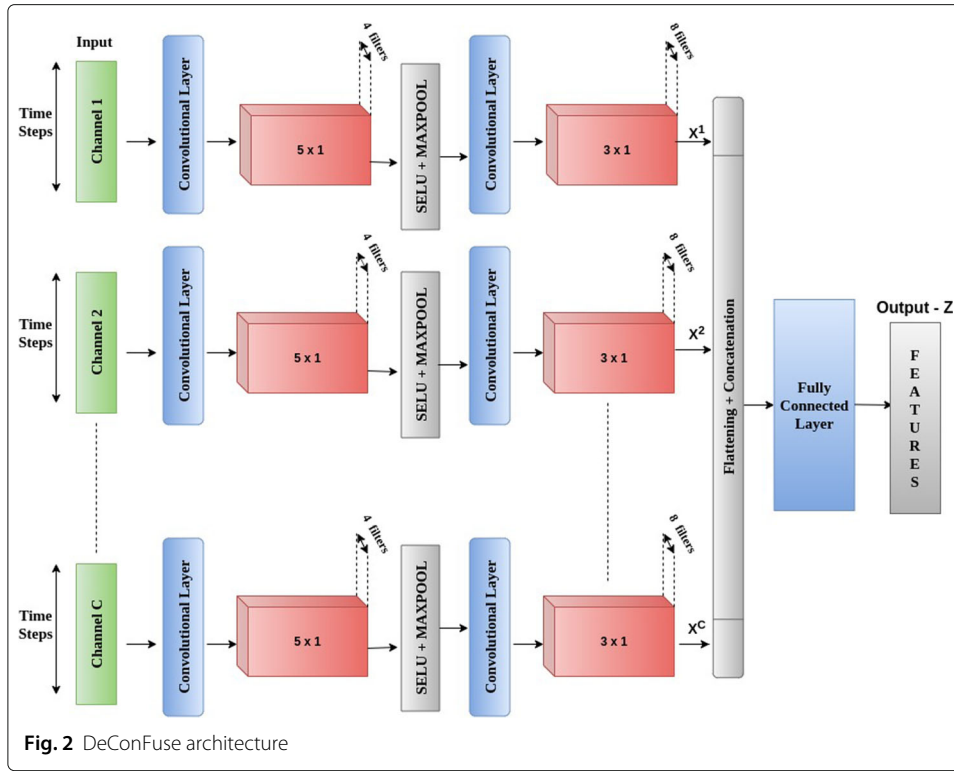
$$F_{\text{conv}}(T_1, \dots, T_L, X | S) = \frac{1}{2} \|T_L * \phi_{L-1}(T_{L-1} * \dots * \phi_1(T_1 * S)) - X\|_F^2 + \Psi(X) + \sum_{\ell=1}^L (\mu \|T_\ell\|_F^2 - \lambda \log \det(T_\ell)). \quad (10)$$

This is a direct extension of the one-layer formulation in (4).

3.2 Multi-channel fusion framework

We now propose a fusion framework to learn in an unsupervised fashion a suitable representation of multi-channel data that can then be utilized for a multitude of tasks. This framework takes the channels of input data samples to separate branches of convolutional layers, leading to multiple sets of channel-wise features. These decoupled features are then concatenated and passed to a fully connected layer, which yields a unique set of coupled features. The complete architecture, called DeConFuse, is shown in Fig. 2.

Since we have multi-channel data, for each channel $c \in \{1, \dots, C\}$, we learn a different set of convolutional filters $T_1^{(c)}, \dots, T_L^{(c)}$ and features $X^{(c)}$. At the same time, we learn the



(not convolutional) linear transform $\tilde{T} = (\tilde{T}_c)_{1 \leq c \leq C}$ to fuse the channel-wise features $X = (X^{(c)})_{1 \leq c \leq C}$, along with the corresponding fused features Z , which constitute the final output of the proposed DeConFuse model, as shown in Fig. 2. This leads to the joint optimization problem

$$\underset{T, X, \tilde{T}, Z}{\text{minimize}} \quad \underbrace{F_{\text{fusion}}(\tilde{T}, Z, X) + \sum_{c=1}^C F_{\text{conv}}(T_1^{(c)}, \dots, T_L^{(c)}, X^{(c)} | S^{(c)})}_{J(T, X, \tilde{T}, Z)} \quad (11)$$

where

$$F_{\text{fusion}}(\tilde{T}, Z, X) = \frac{1}{2} \left\| Z - \sum_{c=1}^C \text{flat}(X^{(c)}) \tilde{T}_c \right\|_F^2 + \iota_+(Z) + \sum_{c=1}^C (\mu \|\tilde{T}_c\|_F^2 - \lambda \log \det(\tilde{T}_c)), \quad (12)$$

where the operator “flat” transforms $X^{(c)}$ into a matrix where each row contains the features of a sample flattened as a vector.

To summarize, our formulation aims to jointly train the channel-wise convolutional filters $T_\ell^{(c)}$ and the fusion coefficients \tilde{T} in an end-to-end fashion. We explicitly learn the features X and Z subject to non-negativity constraints so as to avoid trivial solutions and make our approach completely unsupervised. Moreover, the “log-det” regularization on both $T_\ell^{(c)}$ and \tilde{T} breaks symmetry and forces diversity in the learnt transforms, whereas the Frobenius regularization ensures that the transform coefficients are bounded.

3.3 Optimization algorithm

As for the solution of problem (11), we remark that all terms of the cost function are differentiable, except the indicator function of the non-negativity constraint. We can, therefore, find a local minimizer to (11) by employing the projected gradient descent, whose iterations read

$$\begin{aligned} &\text{For } n = 0, 1, \dots \\ &\begin{cases} T^{[n+1]} = T^{[n]} - \gamma \nabla_T J(T^{[n]}, X^{[n]}, \tilde{T}^{[n]}, Z^{[n]}) \\ X^{[n+1]} = \mathcal{P}_+(X^{[n]} - \gamma \nabla_X J(T^{[n]}, X^{[n]}, \tilde{T}^{[n]}, Z^{[n]})) \\ \tilde{T}^{[n+1]} = \tilde{T}^{[n]} - \gamma \nabla_{\tilde{T}} J(T^{[n]}, X^{[n]}, \tilde{T}^{[n]}, Z^{[n]}) \\ Z^{[n+1]} = \mathcal{P}_+(Z^{[n]} - \gamma \nabla_Z J(T^{[n]}, X^{[n]}, \tilde{T}^{[n]}, Z^{[n]})) \end{cases} \end{aligned} \quad (13)$$

with initialization $T^{[0]}, X^{[0]}, \tilde{T}^{[0]}, Z^{[0]}$, $\gamma > 0$, and $\mathcal{P}_+ = \max\{\cdot, 0\}$. In practice, we make use of accelerated strategies [37] within each step of this algorithm to speed up learning.

There are two notable advantages with the proposed optimization approach. Firstly, we rely on automatic differentiation [38] and stochastic gradient approximations to efficiently solve problem (11). Secondly, we are not limited to ReLU activation in (8), but rather we can use more advanced ones, such as SELU [39]. This is beneficial for the performance, as shown by our numerical results.

3.4 Computational complexity of proposed framework—DeConFuse

Table 1 summarizes the computational complexity of DeConFuse architecture, both for training and test phases. Specifically, it is reported the cost incurred for every input sample at each iteration of gradient descent in the training phase and for the output computation in testing phase. The computational complexity of DeConFuse architecture is comparable to a regular CNN. The only addition is the log-det regularization, which requires to compute the truncated singular value decomposition of $T_\ell^{(c)}$ and \tilde{T}_c . However, as the size of these matrices is determined by the filter size, the number of filters, and the number of output features per sample, the training complexity is not worse than that of a CNN.

4 Experimental evaluation

We carry out experiments on the real-world problem of stock forecasting and trading. The problem of stock forecasting is a regression problem aiming at estimating the price of a stock at a future date (next day for our problem) given inputs till the current date.

Table 1 Time complexity in training and test phases (for one input sample)

Phase	Steps	Time complexity	Dimension description
Training phase	1. Convolution layers	$\mathcal{O}(P_\ell D_\ell M_\ell C)$	
	2. Fully-connected (f.-c.) layer	$\mathcal{O}(I^2 C^2)$	$S^{(c)} \in \mathbb{R}^{K \times D}$
	3. Frobenius norm on conv. layers	$\mathcal{O}(P_\ell M_\ell C)$	$T_\ell^{(c)} \in \mathbb{R}^{P_\ell \times M_\ell}$
	4. Frobenius norm on f.-c. layer	$\mathcal{O}(I^2 C^2)$	$\text{flat}(X^{(c)}) \in \mathbb{R}^{K \times I}$
	5. log-det on conv. layers	$\mathcal{O}(P_\ell^2 M_\ell C)$	$\tilde{T}_c \in \mathbb{R}^{I \times O}$
	6. log-det on f.-c. layer	$\mathcal{O}(I^3 C^2)$	
Testing phase	Step 1. + Step 2.	Step 1. + Step 2.	

D = input sample size – K = num. of samples – C = num. of channels – L = num. of layers

P_ℓ = filter size at layer ℓ – M_ℓ = num. of filters at layer ℓ – D_ℓ = output sample size at layer ℓ

$I = D_L M_L$ is the num. of output features per sample at last convolution layer

$O = \alpha I C$ (with $\alpha \in [0, 1]$) is the num. of output features per sample at the fully connected layer

Stock trading is a classification problem, where the decision whether to buy or sell a stock has to be taken at each time. The two problems are related by the fact that simple logic dictates that if the price of a stock at a later date is expected to increase, the stock must be bought; and if the stock price is expected to go down, the stock must be sold.

We will use the five raw inputs for both the tasks, namely open price, close price, high, low, and net asset value (NAV). One could compute technical indicators based on the raw inputs [19], but in keeping with the essence of true representation learning, we chose to stay with those raw values. Each of the five inputs is processed by a separate 1D processing pipeline. Each of the pipelines produces a flattened output (Fig. 1). The flattened outputs are then concatenated and fed into the transform learning layer acting as the fully connected layer (Fig. 2) for fusion. While our processing pipeline ends here (being unsupervised), the benchmark techniques are supervised and have an output node. The node is binary (buy/sell) for classification and real valued for regression. More precisely, we will compare with two state-of-the-art time series analysis models, namely TimeNet [15] and ConvTimeNet [17]. In the former, the processing individual processing pipelines are based on LSTM and in the later they use 1D CNN.

We make use of a real dataset from the National Stock Exchange (NSE) of India. The dataset contains information of 150 symbols between 2014 and 2018; these stocks were chosen after filtering out stocks that had less than 3 years of data. The companies available in the dataset are from various sectors such as IT (e.g., TCS, INFY), automobile (e.g., HEROMOTOCO, TATAMOTORS), bank (e.g., HDFCBANK, ICICIBANK), coal

Table 2 Description of compared models

Method	Architecture description	Other parameters
DeConFuse	$5 \times \left\{ \begin{array}{l} \text{layer1 : 1D Conv}(1, 4, 5, 1, 2)^1 \\ \text{Maxpool}(2, 2)^2 \\ \text{SELU} \\ \text{layer2 : 1D Conv}(5, 8, 3, 1, 1)^1 \end{array} \right.$ layer3 : Fully connected	Learning rate = 0.001, $\lambda = 0.01$, $\mu = 0.0001$, Optimizer used: Adam **with parameters** $(\beta_1, \beta_2) = (0.9, 0.999)$, weight_decay = 5e-5, epsilon = 1e-8
ConvTimeNet	$5 \times \left\{ \begin{array}{l} \text{layer1 : 1D Convolution}(1, 32, 9, 1, 4)^1 \\ \text{Batch normalization + SELU} \\ \text{layer2 : 1D Convolution}(32, 32, 3, 1, 1)^1 \\ \text{Batch normalization + SELU + SC}^3 \\ \text{layer3 : 1D Convolution}(32, 64, 9, 1, 4)^1 \\ \text{Batch normalization + SELU} \\ \text{layer4 : 1D Convolution}(64, 64, 3, 1, 1)^1 \\ \text{Batch normalization + SELU + SC}^3 \\ \text{layer3 : Global Average Pooling} \end{array} \right.$ layer4 : Fully connected For Trading, added layer5 : Softmax	For forecasting: Learning rate = 0.001, For trading: Learning rate = 0.0001, Optimizer used: Adam **with parameters** $(\beta_1, \beta_2) = (0.9, 0.999)$, weight_decay = 1e-4, epsilon = 1e-8
TimeNet	$5 \times \left\{ \begin{array}{l} \text{layer1 : LSTM unit}(1, 12, 2, \text{True})^4 \\ \text{layer2 : Global Average Pooling} \end{array} \right.$ layer3 : Fully connected For trading, added layer4 : Softmax	For forecasting: Learning Rate = 0.001, For trading: Learning Rate = 0.0005, Optimizer used: Adam **with parameters** $(\beta_1, \beta_2) = (0.9, 0.999)$, weight_decay = 5e-5, epsilon = 1e-8

¹ (in_planes, out_planes, kernel_size, stride, padding)

² (kernel_size, stride)

³ SC - Skip-Connection

⁴ (input_size, hidden_size, #layers, bidirectional)

and petroleum (e.g., OIL, ONGC), steel (e.g., JSWSTEEL, TATASTEEL), construction (e.g., ABIRLANUVO, ACC), and public sector units (e.g., POWERGRID, GAIL). The detailed architectures for each tested techniques, namely DeConFuse, ConvTimeNet, and TimeNet, are presented in Table 2. For DeConFuse, TimeNet, and ConvTimeNet, we have tuned the architectures to yield the best performance and have randomly initialized the weights for each stock's training.

4.1 Stock forecasting—regression

Let us start with the stock forecasting problem. We feed the generated unsupervised features from the proposed architecture into an external regressor, namely ridge regression. Evaluation is carried out in terms of mean absolute error (MAE) between the predicted and actual stock prices for all 150 stocks. The stock forecasting results are shown in Table 5 in Appendix 1 section. The MAE for individual stocks are presented for each of close price, open price, high price, low price, and net asset value.

From Table 5 in Appendix 1 section, it can be seen that the MAE values reached for the proposed DeConFuse solution for the four first prices (open, close, high, low) are exceptionally good for all of the 150 stocks. Regarding NAV prediction, the proposed method performs extremely well for 128 stocks. For the remaining 22 stocks, there are 13 stocks, highlighted in red, for which DeConFuse does not give the lowest MAE but it is still very close to the best results given by the TimeNet approach.

For a concise summary of the results, the average values over all stocks are shown in Table 3.

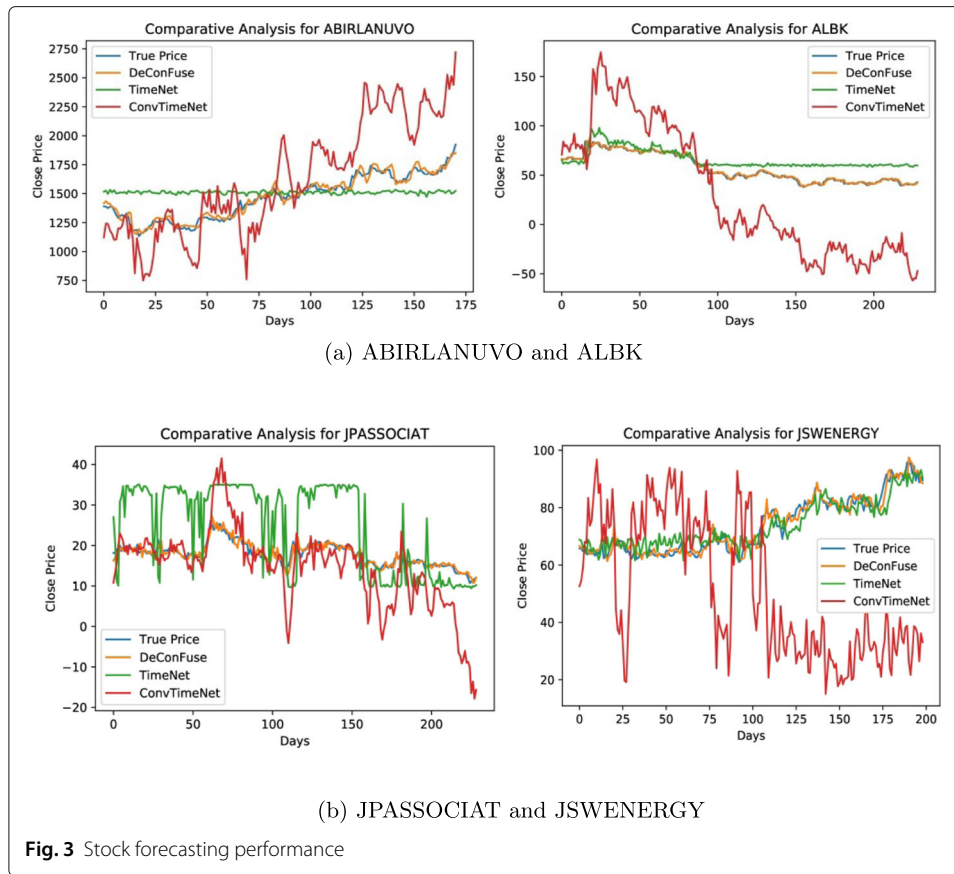
From the summary Table 3, it can be observed that our error is more than an order of magnitude better than the state of the arts. The plots for one of the regressed prices (close price) for some examples of stocks in Fig. 3 show that the predicted close prices from DeConFuse are closer to the true close prices than benchmark predictions.

4.2 Stock trading—classification

We now focus on the stock trading task. In this case, the generated unsupervised features from DeConFuse are inputs to an external classifier based on random decision forest (RDF) with 5 decision tree classifiers and depth 3. Even though we used this architecture, we found that the results from RDF are robust to changes in architecture. This is a well known phenomenon about RDFs [40]. We evaluate the results in terms of precision, recall, F1 score, and area under the ROC curve (AUC). From the financial viewpoint, we also calculate annualized returns (AR) using the predicted trading signals/labels as well as using true trading signals/labels named as predicted AR and true AR, respectively. The starting capital used for calculating AR values for every stock is Rs. 100,000 and the transaction charges are Rs 10. The stock trading results are shown in Table 6 in Appendix 2 section.

Table 3 Summary of forecasting results

Method	Close	Open	High	Low	NAV
DeConFuse	0.016	0.007	0.012	0.013	0.410
ConvTimeNet	1.550	1.550	1.530	1.560	2.350
TimeNet	0.295	0.295	0.294	0.295	0.511



Certain results from Table 6 in [Appendix 2](#) section are highlighted in bold or red. The first set of results, marked in bold, are the ones where one of the techniques for each metric gives the best performance for each stock. The proposed solution DeConFuse gives the best results for 89 stocks for precision score, 85 stocks for recall score, 125 stocks for F1 score, 91 stocks for AUC measure, and 56 stocks in case of the AR metric. The other set marked in red highlights the cases where DeConFuse has not performed the best but performs nearly equal (here, a difference of maximum 0.05 in the metric is considered) to the best performance given by one of the benchmarks, i.e., DeConFuse gives the next best performance. We noticed that there are 24 stocks for which DeConFuse gives the next best precision metric value. Likewise, 18 stocks in case of recall, 22 stocks for F1 score, 26 stocks for AUC values, and 1 stock in case of AR. Overall, DeConFuse reaches a very satisfying performance over the benchmark techniques. This is also corroborated from the summary of trading results in Table 4.

Table 4 Summary of trading results

Method	Precision	Recall	F1 score	AUC	MAE AR
DeConFuse	0.520	0.810	0.628	0.543	17.350
ConvTimeNet	0.510	0.457	0.413	0.524	19.410
TimeNet	0.470	0.648	0.490	0.513	18.760

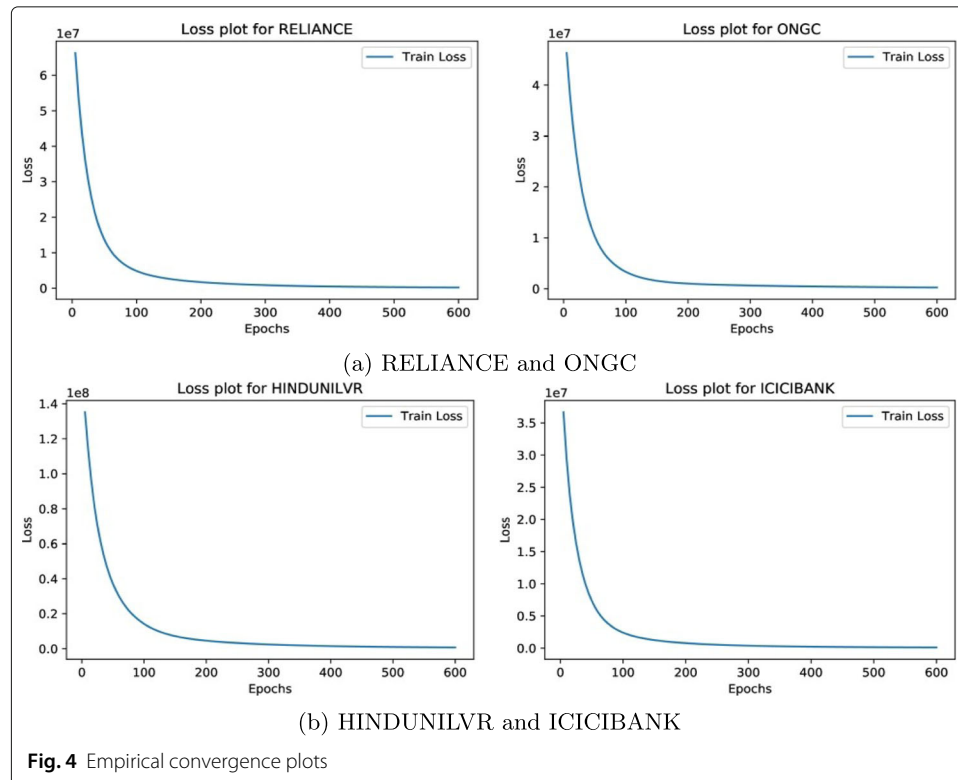
We also display empirical convergence plots for few stocks, namely RELIANCE, ONGC, HINDUNILVR, and ICICIBANK, in Fig. 4. We can see that the training loss decreases to a point of stability for each example.

5 Conclusion

In this work, we propose DeConFuse, a deep fusion end-to-end framework for the processing of 1D multi-channel data. Unlike other deep learning models, our framework is unsupervised. It is based on a novel deep version of our recently proposed convolutional transform learning model. We have applied the proposed model for stock forecasting/trading leading to very good performance. The framework is generic enough to handle other multi-channel fusion problems as well.

The advantage of our framework is its ability to learn in an unsupervised fashion. For example, consider the problem we address. For traditional deep learning-based models, we need to retrain to deep networks for regression and classification. But we can reuse our features for both the tasks, without the requirement of re-training, for specific tasks. This has advantages in other areas as well. For example, one can either do ischemia detection, i.e., detect whether one is having a stroke at the current time instant (from EEG); or one can do ischemia prediction, i.e., forecast if a stroke is going to happen. In standard deep learning, two networks need to be retrained and tuned to tackle these two problems. With our proposed method, there is no need for this double effort.

In the future, we would work on extending the framework for supervised/semi-supervised formulations. We believe that the semi-supervised formulation will be of immense practical importance. We would also like to extend it to 2D convolutions in order to handle image data.



Appendix 1: Detailed stock forecasting results

Table 5 Stock-wise forecasting results

Stock name	Method	MAE close	MAE open	MAE high	MAE low	MAE NAV
ABIRLANUVO	DeConFuse	0.021	0.015	0.019	0.017	0.416
	ConvTimeNet	0.204	0.212	0.219	0.195	1.804
	TimeNet	0.112	0.111	0.111	0.112	0.467
ACC	DeConFuse	0.012	0.016	0.014	0.017	0.580
	ConvTimeNet	0.158	0.161	0.159	0.158	0.765
	TimeNet	0.116	0.116	0.115	0.118	0.388
ADANIENT	DeConFuse	0.041	0.015	0.024	0.038	0.359
	ConvTimeNet	4.656	4.795	4.654	4.800	0.748
	TimeNet	0.538	0.549	0.540	0.551	0.475
ADANIPOWER	DeConFuse	0.012	0.005	0.009	0.010	0.391
	ConvTimeNet	0.124	0.122	0.122	0.123	1.258
	TimeNet	0.283	0.283	0.280	0.285	0.43
ADANIPHARM	DeConFuse	0.026	0.010	0.019	0.020	0.405
	ConvTimeNet	0.610	0.600	0.590	0.602	1.796
	TimeNet	0.205	0.205	0.204	0.206	0.448
ALBK	DeConFuse	0.016	0.007	0.012	0.012	0.418
	ConvTimeNet	0.401	0.374	0.384	0.400	0.867
	TimeNet	0.262	0.261	0.258	0.264	0.480
AMARAJABAT	DeConFuse	0.020	0.009	0.015	0.015	0.362
	ConvTimeNet	0.908	1.029	0.995	0.953	1.020
	TimeNet	0.184	0.181	0.180	0.185	0.448
AMBUJACEM	DeConFuse	0.015	0.007	0.011	0.012	0.435
	ConvTimeNet	0.047	0.046	0.047	0.047	0.631
	TimeNet	0.087	0.088	0.086	0.089	0.386
ANDHRABANK	DeConFuse	0.012	0.005	0.008	0.009	0.355
	ConvTimeNet	2.283	2.272	2.280	2.267	3.132
	TimeNet	0.106	0.107	0.105	0.107	0.414
APOLLOHOSP	DeConFuse	0.022	0.009	0.016	0.016	0.373
	ConvTimeNet	5.095	5.074	5.008	5.158	2.200
	TimeNet	0.144	0.140	0.138	0.148	0.471
APOLLOTYRE	DeConFuse	0.025	0.009	0.015	0.021	0.687
	ConvTimeNet	0.268	0.240	0.258	0.254	0.719
	TimeNet	0.153	0.155	0.151	0.156	0.536
ARVIND	DeConFuse	0.014	0.006	0.010	0.011	0.391
	ConvTimeNet	0.552	0.547	0.543	0.558	1.267
	TimeNet	0.283	0.283	0.281	0.284	0.346
ASHOKLEY	DeConFuse	0.015	0.006	0.010	0.011	0.423
	ConvTimeNet	0.302	0.278	0.294	0.290	1.251
	TimeNet	0.268	0.268	0.267	0.269	0.465
ASIANPAINT	DeConFuse	0.017	0.005	0.010	0.013	0.376
	ConvTimeNet	1.042	1.018	0.987	1.096	0.586
	TimeNet	0.343	0.343	0.344	0.342	0.451
AUROPHARMA	DeConFuse	0.008	0.004	0.007	0.006	0.370
	ConvTimeNet	0.816	0.801	0.804	0.816	1.272
	TimeNet	0.290	0.289	0.288	0.290	0.465
	DeConFuse	0.015	0.005	0.009	0.010	0.312
	ConvTimeNet	1.802	1.847	1.801	1.829	1.034
	TimeNet	0.075	0.076	0.075	0.076	0.393

Table 5 Stock-wise forecasting results (Continued)

Stock name	Method	MAE close	MAE open	MAE high	MAE low	MAE NAV
BAJAJ-AUTO	DeConFuse	0.012	0.007	0.009	0.010	0.392
	ConvTimeNet	0.329	0.326	0.328	0.327	0.580
	TimeNet	0.175	0.176	0.175	0.176	0.466
BAJFINANCE	DeConFuse	0.013	0.004	0.009	0.009	0.361
	ConvTimeNet	2.519	2.518	2.534	2.506	2.575
	TimeNet	0.509	0.509	0.508	0.510	0.693
BANKBARODA	DeConFuse	0.021	0.007	0.015	0.014	0.299
	ConvTimeNet	0.891	0.860	0.849	0.887	0.845
	TimeNet	0.130	0.131	0.130	0.132	0.402
BANKINDIA	DeConFuse	0.022	0.009	0.016	0.016	0.354
	ConvTimeNet	2.451	2.437	2.449	2.441	1.351
	TimeNet	0.374	0.375	0.373	0.375	0.384
BATAINDIA	DeConFuse	0.015	0.009	0.012	0.011	0.391
	ConvTimeNet	0.143	0.111	0.129	0.125	1.095
	TimeNet	0.301	0.299	0.299	0.301	0.477
BEL	DeConFuse	0.019	0.007	0.013	0.014	0.366
	ConvTimeNet	1.576	1.537	1.524	1.622	3.338
	TimeNet	0.145	0.146	0.142	0.148	0.410
BHARATFORG	DeConFuse	0.013	0.006	0.009	0.01	0.567
	ConvTimeNet	3.207	3.178	3.162	3.219	7.468
	TimeNet	0.345	0.345	0.343	0.347	0.555
BHARTIARTL	DeConFuse	0.019	0.012	0.015	0.016	0.381
	ConvTimeNet	1.849	1.809	1.817	1.841	1.042
	TimeNet	0.167	0.167	0.168	0.166	0.500
BHEL	DeConFuse	0.016	0.007	0.012	0.012	0.765
	ConvTimeNet	2.664	2.613	2.660	2.617	8.514
	TimeNet	0.389	0.389	0.391	0.386	0.928
BIOCON	DeConFuse	0.016	0.007	0.013	0.012	0.450
	ConvTimeNet	1.338	1.287	1.303	1.330	1.031
	TimeNet	0.604	0.603	0.604	0.602	0.470
BOSCHLTD	DeConFuse	0.012	0.005	0.009	0.007	0.516
	ConvTimeNet	0.158	0.158	0.159	0.155	0.600
	TimeNet	0.724	0.723	0.727	0.721	0.551
BPCL	DeConFuse	0.014	0.006	0.010	0.011	0.323
	ConvTimeNet	0.243	0.267	0.267	0.244	1.614
	TimeNet	0.276	0.277	0.276	0.276	0.374
BRITANNIA	DeConFuse	0.009	0.004	0.006	0.006	0.367
	ConvTimeNet	0.800	0.828	0.813	0.812	1.442
	TimeNet	0.414	0.413	0.413	0.413	0.450
CAIRN	DeConFuse	0.016	0.008	0.011	0.013	0.334
	ConvTimeNet	3.945	3.988	3.939	4.025	0.969
	TimeNet	0.159	0.159	0.159	0.158	0.345
CANBK	DeConFuse	0.021	0.008	0.015	0.015	0.276
	ConvTimeNet	2.140	2.023	2.065	2.100	0.806
	TimeNet	0.151	0.153	0.151	0.154	0.444
CASTROLIND	DeConFuse	0.014	0.005	0.010	0.011	0.523
	ConvTimeNet	2.055	2.107	2.036	2.162	12.249
	TimeNet	0.141	0.141	0.141	0.143	0.527
CEATLTD	DeConFuse	0.015	0.006	0.010	0.011	0.319
	ConvTimeNet	2.341	2.308	2.295	2.344	1.118
	TimeNet	0.160	0.163	0.161	0.162	0.326

Table 5 Stock-wise forecasting results (Continued)

Stock name	method	MAE close	MAE open	MAE high	MAE low	MAE NAV
CENTURYTEX	DeConFuse	0.015	0.006	0.010	0.013	0.404
	ConvTimeNet	1.111	1.072	1.106	1.083	2.685
	TimeNet	0.405	0.406	0.404	0.407	0.352
CESC	DeConFuse	0.013	0.005	0.009	0.010	0.404
	ConvTimeNet	0.390	0.377	0.374	0.395	0.602
	TimeNet	0.364	0.363	0.362	0.364	0.477
CIPLA	DeConFuse	0.012	0.004	0.009	0.008	0.408
	ConvTimeNet	2.063	2.074	2.052	2.066	0.695
	TimeNet	0.064	0.064	0.063	0.065	0.476
COALINDIA	DeConFuse	0.012	0.005	0.009	0.009	0.393
	ConvTimeNet	1.635	1.737	1.632	1.723	2.791
	TimeNet	0.154	0.156	0.155	0.154	0.474
COLPAL	DeConFuse	0.009	0.004	0.006	0.007	0.553
	ConvTimeNet	0.115	0.119	0.114	0.117	1.158
	TimeNet	0.164	0.164	0.164	0.165	0.566
DABUR	DeConFuse	0.010	0.005	0.008	0.008	0.474
	ConvTimeNet	1.369	1.398	1.360	1.409	1.530
	TimeNet	0.271	0.269	0.270	0.271	0.539
DHFL	DeConFuse	0.016	0.007	0.012	0.012	0.471
	ConvTimeNet	0.302	0.285	0.291	0.289	1.118
	TimeNet	0.456	0.456	0.457	0.457	0.657
DISHTV	DeConFuse	0.016	0.006	0.013	0.012	0.478
	ConvTimeNet	0.722	0.733	0.742	0.708	1.948
	TimeNet	0.224	0.225	0.225	0.224	0.586
DIVISLAB	DeConFuse	0.014	0.006	0.012	0.010	0.508
	ConvTimeNet	0.183	0.195	0.190	0.190	0.871
	TimeNet	0.160	0.159	0.161	0.159	0.422
DLF	DeConFuse	0.021	0.012	0.015	0.018	0.318
	ConvTimeNet	1.053	1.104	1.053	1.100	0.590
	TimeNet	0.311	0.309	0.308	0.312	0.402
DRREDDY	DeConFuse	0.013	0.006	0.010	0.010	0.393
	ConvTimeNet	0.213	0.210	0.210	0.210	0.628
	TimeNet	0.373	0.373	0.37	0.374	0.505
EICHERMOT	DeConFuse	0.012	0.004	0.008	0.008	0.363
	ConvTimeNet	0.295	0.296	0.295	0.297	0.452
	TimeNet	0.816	0.816	0.818	0.814	0.393
ENGINEERSIN	DeConFuse	0.023	0.019	0.020	0.022	0.452
	ConvTimeNet	0.265	0.260	0.258	0.260	2.059
	TimeNet	0.128	0.128	0.128	0.128	0.500
EXIDEIND	DeConFuse	0.012	0.005	0.009	0.009	0.418
	ConvTimeNet	0.442	0.453	0.449	0.448	1.209
	TimeNet	0.265	0.263	0.263	0.265	0.420
FEDERALBNK	DeConFuse	0.015	0.006	0.010	0.012	0.407
	ConvTimeNet	2.405	2.345	2.360	2.378	1.292
	TimeNet	0.146	0.148	0.147	0.147	0.502
GAIL	DeConFuse	0.014	0.009	0.011	0.012	0.369
	ConvTimeNet	0.209	0.169	0.182	0.195	1.070
	TimeNet	0.330	0.330	0.330	0.330	0.394
GLENMARK	DeConFuse	0.013	0.005	0.010	0.009	0.374
	ConvTimeNet	0.614	0.675	0.612	0.666	2.597
	TimeNet	0.399	0.401	0.402	0.397	0.448

Table 5 Stock-wise forecasting results (Continued)

Stock name	Method	MAE close	MAE open	MAE high	MAE low	MAE NAV
GMRINFRA	DeConFuse	0.029	0.017	0.023	0.024	0.616
	ConvTimeNet	0.101	0.137	0.118	0.116	1.044
	TimeNet	0.094	0.092	0.095	0.094	0.799
GODREJIND	DeConFuse	0.012	0.008	0.010	0.011	0.376
	ConvTimeNet	0.287	0.298	0.28	0.296	1.647
	TimeNet	0.327	0.326	0.325	0.328	0.362
GRASIM	DeConFuse	0.014	0.008	0.011	0.011	0.445
	ConvTimeNet	0.307	0.318	0.309	0.312	1.289
	TimeNet	0.259	0.259	0.259	0.257	0.386
HAVELLS	DeConFuse	0.012	0.005	0.009	0.009	0.377
	ConvTimeNet	0.426	0.410	0.422	0.421	1.182
	TimeNet	0.403	0.402	0.402	0.404	0.400
HCLTECH	DeConFuse	0.014	0.010	0.011	0.014	0.383
	ConvTimeNet	1.854	1.839	1.818	1.853	1.457
	TimeNet	0.113	0.113	0.113	0.114	0.442
HDFC	DeConFuse	0.009	0.004	0.006	0.006	0.314
	ConvTimeNet	0.747	0.713	0.734	0.746	1.239
	TimeNet	0.318	0.319	0.317	0.321	0.383
HDFCBANK	DeConFuse	0.007	0.003	0.005	0.005	0.330
	ConvTimeNet	0.529	0.533	0.533	0.544	3.680
	TimeNet	0.422	0.422	0.421	0.423	0.576
HDIL	DeConFuse	0.027	0.014	0.021	0.022	0.624
	ConvTimeNet	0.300	0.560	0.352	0.439	10.715
	TimeNet	0.297	0.291	0.290	0.296	1.106
HEROMOTOCO	DeConFuse	0.009	0.004	0.006	0.006	0.322
	ConvTimeNet	0.129	0.134	0.129	0.134	0.810
	TimeNet	0.191	0.192	0.190	0.193	0.416
HEXAWARE	DeConFuse	0.017	0.007	0.012	0.013	0.496
	ConvTimeNet	2.798	2.710	2.691	2.769	1.050
	TimeNet	0.425	0.422	0.424	0.423	0.473
HINDALCO	DeConFuse	0.016	0.007	0.012	0.012	0.310
	ConvTimeNet	0.984	0.995	0.979	1.002	1.159
	TimeNet	0.403	0.403	0.402	0.404	0.388
HINDPETRO	DeConFuse	0.016	0.007	0.012	0.012	0.37
	ConvTimeNet	0.998	0.961	0.965	0.999	1.545
	TimeNet	0.375	0.377	0.376	0.376	0.397
HINDUNILVR	DeConFuse	0.008	0.003	0.006	0.006	0.413
	ConvTimeNet	0.181	0.153	0.151	0.183	0.997
	TimeNet	0.414	0.413	0.413	0.415	0.427
HINDZINC	DeConFuse	0.012	0.006	0.009	0.010	0.333
	ConvTimeNet	0.057	0.063	0.062	0.055	2.246
	TimeNet	0.346	0.346	0.344	0.347	0.362
IBREALEST	DeConFuse	0.033	0.026	0.031	0.028	0.694
	ConvTimeNet	6.230	6.588	6.338	6.375	6.639
	TimeNet	0.612	0.611	0.613	0.611	0.662
IBULHSGFIN	DeConFuse	0.014	0.006	0.011	0.011	0.381
	ConvTimeNet	0.352	0.341	0.343	0.354	0.556
	TimeNet	0.357	0.358	0.356	0.358	0.584
ICICIBANK	DeConFuse	0.016	0.012	0.014	0.014	0.314
	ConvTimeNet	2.773	2.801	2.766	2.784	1.126
	TimeNet	0.156	0.155	0.156	0.155	0.609

Table 5 Stock-wise forecasting results (Continued)

Stock name	Method	MAE close	MAE open	MAE high	MAE low	MAE NAV
IDBI	DeConFuse	0.026	0.010	0.019	0.018	0.408
	ConvTimeNet	0.900	0.909	0.846	0.952	1.995
	TimeNet	0.135	0.137	0.134	0.138	0.550
IDEA	DeConFuse	0.022	0.008	0.015	0.015	0.396
	ConvTimeNet	1.612	1.684	1.629	1.671	1.676
	TimeNet	0.576	0.575	0.569	0.580	0.454
IDFC	DeConFuse	0.017	0.008	0.012	0.013	0.523
	ConvTimeNet	0.693	0.674	0.629	0.748	5.201
	TimeNet	0.134	0.135	0.134	0.134	0.680
IFCI	DeConFuse	0.024	0.009	0.020	0.016	0.623
	ConvTimeNet	0.807	0.744	0.837	0.755	10.316
	TimeNet	0.244	0.243	0.246	0.245	0.967
IGL	DeConFuse	0.015	0.005	0.011	0.011	0.490
	ConvTimeNet	0.264	0.255	0.257	0.264	1.324
	TimeNet	0.348	0.350	0.350	0.346	0.369
INDIACEM	DeConFuse	0.023	0.014	0.018	0.020	0.360
	ConvTimeNet	0.712	0.689	0.692	0.705	1.012
	TimeNet	0.149	0.150	0.148	0.150	0.360
INDUSINDBK	DeConFuse	0.009	0.004	0.006	0.006	0.315
	ConvTimeNet	0.502	0.509	0.507	0.500	1.253
	TimeNet	0.453	0.453	0.452	0.454	0.419
INFY	DeConFuse	0.010	0.005	0.008	0.008	0.405
	ConvTimeNet	2.417	2.415	2.410	2.409	1.837
	TimeNet	0.140	0.139	0.14	0.139	0.605
IOC	DeConFuse	0.012	0.006	0.010	0.011	0.369
	ConvTimeNet	0.334	0.285	0.309	0.327	1.359
	TimeNet	0.205	0.206	0.204	0.206	0.392
IRB	DeConFuse	0.019	0.007	0.014	0.014	0.475
	ConvTimeNet	0.365	0.360	0.355	0.380	1.583
	TimeNet	0.076	0.076	0.077	0.076	0.580
ITC	DeConFuse	0.009	0.004	0.007	0.006	0.383
	ConvTimeNet	0.539	0.545	0.549	0.540	1.089
	TimeNet	0.106	0.106	0.105	0.108	0.457
JINDALSTEL	DeConFuse	0.029	0.017	0.023	0.024	0.337
	ConvTimeNet	6.234	6.467	6.223	6.34	5.342
	TimeNet	0.394	0.392	0.392	0.394	0.565
JISLJALEQS	DeConFuse	0.022	0.008	0.014	0.018	0.461
	ConvTimeNet	0.965	0.969	0.953	0.976	1.066
	TimeNet	0.238	0.237	0.238	0.236	0.474
JPASSOCIAT	DeConFuse	0.046	0.028	0.035	0.040	0.675
	ConvTimeNet	0.321	0.318	0.309	0.321	1.660
	TimeNet	0.565	0.567	0.563	0.568	1.227
JSWENERGY	DeConFuse	0.024	0.019	0.023	0.021	0.610
	ConvTimeNet	0.453	0.462	0.438	0.469	1.320
	TimeNet	0.045	0.044	0.044	0.044	0.621
JSWSTEEL	DeConFuse	0.014	0.006	0.011	0.010	0.304
	ConvTimeNet	1.093	1.206	1.093	1.135	1.895
	TimeNet	0.535	0.534	0.535	0.535	0.365
JUBLFOOD	DeConFuse	0.013	0.006	0.010	0.011	0.409
	ConvTimeNet	7.716	7.395	7.521	7.733	3.604
	TimeNet	0.442	0.441	0.44	0.443	0.672

Table 5 Stock-wise forecasting results (Continued)

Stock name	Method	MAE close	MAE open	MAE high	MAE low	MAE NAV
JUSTDIAL	DeConFuse	0.026	0.009	0.018	0.020	0.473
	ConvTimeNet	7.726	7.839	7.787	7.856	3.06
	TimeNet	0.738	0.745	0.735	0.750	0.505
KOTAKBANK	DeConFuse	0.009	0.004	0.007	0.007	0.342
	ConvTimeNet	0.278	0.294	0.258	0.307	5.970
	TimeNet	0.401	0.400	0.399	0.402	0.349
KSCL	DeConFuse	0.016	0.006	0.011	0.012	0.503
	ConvTimeNet	0.240	0.252	0.235	0.242	1.831
	TimeNet	0.089	0.086	0.085	0.090	0.739
KTKBANK	DeConFuse	0.016	0.006	0.012	0.013	0.452
	ConvTimeNet	2.447	2.452	2.430	2.464	1.224
	TimeNet	0.124	0.125	0.123	0.126	0.504
L&TFH	DeConFuse	0.017	0.006	0.011	0.012	0.366
	ConvTimeNet	0.343	0.345	0.339	0.351	0.741
	TimeNet	0.466	0.467	0.468	0.465	0.416
LICHSGFIN	DeConFuse	0.013	0.005	0.009	0.010	0.354
	ConvTimeNet	1.587	1.604	1.591	1.584	1.971
	TimeNet	0.126	0.127	0.126	0.128	0.400
LT	DeConFuse	0.010	0.005	0.007	0.008	0.372
	ConvTimeNet	0.877	0.858	0.851	0.877	0.732
	TimeNet	0.222	0.222	0.221	0.224	0.338
LUPIN	DeConFuse	0.014	0.004	0.009	0.010	0.406
	ConvTimeNet	0.687	0.658	0.678	0.663	1.229
	TimeNet	0.707	0.706	0.705	0.706	0.514
M&M	DeConFuse	0.014	0.008	0.010	0.011	0.361
	ConvTimeNet	2.729	2.723	2.713	2.684	1.088
	TimeNet	0.207	0.207	0.206	0.208	0.413
M&MFIN	DeConFuse	0.018	0.011	0.014	0.016	0.356
	ConvTimeNet	1.800	1.789	1.795	1.807	1.489
	TimeNet	0.371	0.370	0.371	0.372	0.358
MARUTI	DeConFuse	0.009	0.003	0.006	0.006	0.356
	ConvTimeNet	0.253	0.249	0.248	0.254	1.103
	TimeNet	0.542	0.542	0.542	0.542	0.546
MINDTREE	DeConFuse	0.019	0.010	0.015	0.013	0.491
	ConvTimeNet	0.594	0.559	0.545	0.599	1.058
	TimeNet	0.319	0.318	0.319	0.317	0.770
MOTHERSUMI	DeConFuse	0.014	0.005	0.009	0.011	0.381
	ConvTimeNet	0.954	0.995	0.962	0.964	0.955
	TimeNet	0.388	0.389	0.388	0.39	0.413
MRF	DeConFuse	0.010	0.004	0.007	0.008	0.597
	ConvTimeNet	0.422	0.421	0.420	0.423	0.618
	TimeNet	0.915	0.915	0.916	0.914	0.489
NHPC	DeConFuse	0.012	0.006	0.010	0.010	0.608
	ConvTimeNet	2.957	3.029	2.986	3.006	9.161
	TimeNet	0.083	0.082	0.083	0.084	0.706
NMDC	DeConFuse	0.018	0.012	0.015	0.016	0.385
	ConvTimeNet	0.747	0.743	0.741	0.746	1.214
	TimeNet	0.103	0.103	0.105	0.101	0.491
NTPC	DeConFuse	0.009	0.007	0.008	0.008	0.370
	ConvTimeNet	0.507	0.507	0.515	0.499	1.082
	TimeNet	0.111	0.110	0.110	0.112	0.563

Table 5 Stock-wise forecasting results (Continued)

Stock name	Method	MAE close	MAE open	MAE high	MAE low	MAE NAV
OFSS	DeConFuse	0.012	0.007	0.009	0.009	0.590
	ConvTimeNet	0.144	0.158	0.150	0.152	0.727
	TimeNet	0.105	0.103	0.105	0.103	0.552
OIL	DeConFuse	0.014	0.007	0.010	0.012	0.441
	ConvTimeNet	0.294	0.271	0.283	0.279	1.602
	TimeNet	0.068	0.070	0.070	0.069	0.455
ONGC	DeConFuse	0.012	0.006	0.009	0.010	0.467
	ConvTimeNet	5.154	5.167	5.140	5.171	1.673
	TimeNet	0.074	0.075	0.076	0.073	0.548
ORIENTBANK	DeConFuse	0.023	0.009	0.017	0.016	0.378
	ConvTimeNet	1.706	1.565	1.632	1.63	6.662
	TimeNet	0.673	0.675	0.674	0.674	0.725
PAGEIND	DeConFuse	0.017	0.006	0.013	0.010	0.431
	ConvTimeNet	0.377	0.376	0.377	0.377	0.862
	TimeNet	0.824	0.823	0.826	0.821	0.655
PETRONET	DeConFuse	0.014	0.006	0.011	0.011	0.494
	ConvTimeNet	0.785	0.793	0.793	0.787	3.480
	TimeNet	0.119	0.118	0.118	0.118	0.455
PFC	DeConFuse	0.019	0.011	0.015	0.016	0.335
	ConvTimeNet	6.082	6.160	6.127	6.107	5.328
	TimeNet	0.208	0.208	0.206	0.209	0.377
PIDILITIND	DeConFuse	0.011	0.006	0.008	0.008	0.339
	ConvTimeNet	0.148	0.159	0.158	0.148	1.693
	TimeNet	0.328	0.327	0.328	0.328	0.514
PNB	DeConFuse	0.025	0.010	0.019	0.017	0.402
	ConvTimeNet	9.020	9.009	8.898	9.059	4.502
	TimeNet	0.358	0.357	0.357	0.358	0.593
POWERGRID	DeConFuse	0.009	0.006	0.007	0.008	0.351
	ConvTimeNet	1.329	1.354	1.321	1.359	4.055
	TimeNet	0.196	0.196	0.194	0.197	0.412
PTC	DeConFuse	0.016	0.007	0.011	0.012	0.385
	ConvTimeNet	1.190	1.146	1.140	1.190	1.877
	TimeNet	0.187	0.188	0.187	0.187	0.353
RCOM	DeConFuse	0.049	0.019	0.040	0.033	0.515
	ConvTimeNet	11.473	11.273	11.142	11.890	2.267
	TimeNet	0.363	0.360	0.344	0.377	0.581
RECLTD	DeConFuse	0.017	0.005	0.012	0.012	0.401
	ConvTimeNet	7.043	6.659	6.798	6.912	12.186
	TimeNet	0.145	0.145	0.144	0.147	0.521
RELCAPITAL	DeConFuse	0.025	0.014	0.018	0.021	0.302
	ConvTimeNet	2.394	2.359	2.289	2.428	0.498
	TimeNet	0.127	0.130	0.128	0.131	0.474
RELIANCE	DeConFuse	0.011	0.004	0.008	0.008	0.305
	ConvTimeNet	0.251	0.234	0.245	0.239	1.609
	TimeNet	0.459	0.458	0.458	0.459	0.654
RELINFRA	DeConFuse	0.019	0.007	0.013	0.014	0.270
	ConvTimeNet	2.045	2.032	1.998	2.084	0.970
	TimeNet	0.157	0.159	0.157	0.159	0.320
RPOWER	DeConFuse	0.024	0.007	0.018	0.016	0.475
	ConvTimeNet	2.229	2.178	2.159	2.268	2.384
	TimeNet	0.296	0.297	0.295	0.302	0.757

Table 5 Stock-wise forecasting results (Continued)

Stock name	Method	MAE close	MAE open	MAE high	MAE low	MAE NAV
SAIL	DeConFuse	0.023	0.008	0.014	0.016	0.284
	ConvTimeNet	1.319	1.225	1.274	1.276	1.399
	TimeNet	0.161	0.160	0.163	0.158	0.495
SBIN	DeConFuse	0.015	0.006	0.011	0.01	0.339
	ConvTimeNet	0.663	0.661	0.675	0.648	1.428
	TimeNet	0.120	0.118	0.120	0.118	0.696
SIEMENS	DeConFuse	0.011	0.006	0.008	0.009	0.452
	ConvTimeNet	0.289	0.212	0.292	0.245	8.495
	TimeNet	0.085	0.086	0.085	0.086	0.763
SOUTHBANK	DeConFuse	0.018	0.008	0.013	0.013	0.539
	ConvTimeNet	7.863	7.712	7.795	7.788	10.684
	TimeNet	0.162	0.161	0.161	0.163	0.534
SRF	DeConFuse	0.016	0.006	0.011	0.012	0.396
	ConvTimeNet	0.373	0.318	0.339	0.359	0.791
	TimeNet	0.226	0.225	0.225	0.225	0.508
SRTRANSFIN	DeConFuse	0.019	0.011	0.015	0.017	0.445
	ConvTimeNet	2.900	2.892	2.838	2.946	0.667
	TimeNet	0.297	0.295	0.296	0.297	0.482
STAR	DeConFuse	0.027	0.015	0.022	0.025	0.464
	ConvTimeNet	2.461	2.586	2.307	2.629	6.115
	TimeNet	0.827	0.820	0.821	0.825	0.642
SUNPHARMA	DeConFuse	0.016	0.006	0.011	0.011	0.368
	ConvTimeNet	0.203	0.202	0.203	0.203	0.655
	TimeNet	0.388	0.390	0.385	0.391	0.645
SUNTV	DeConFuse	0.015	0.005	0.010	0.011	0.356
	ConvTimeNet	0.175	0.172	0.173	0.176	1.482
	TimeNet	0.471	0.472	0.470	0.472	0.483
SYNDIBANK	DeConFuse	0.024	0.009	0.017	0.017	0.361
	ConvTimeNet	1.405	1.391	1.271	1.521	4.672
	TimeNet	0.176	0.175	0.174	0.177	0.410
TATACHEM	DeConFuse	0.011	0.005	0.008	0.009	0.392
	ConvTimeNet	1.044	1.066	1.044	1.025	0.690
	TimeNet	0.368	0.368	0.367	0.368	0.412
TATACOMM	DeConFuse	0.013	0.006	0.009	0.010	0.443
	ConvTimeNet	0.231	0.249	0.239	0.241	0.835
	TimeNet	0.241	0.241	0.239	0.243	0.541
TATAGLOBAL	DeConFuse	0.017	0.006	0.013	0.012	0.599
	ConvTimeNet	1.724	1.807	1.737	1.813	4.354
	TimeNet	0.418	0.417	0.418	0.416	0.477
TATAMOTORS	DeConFuse	0.015	0.007	0.012	0.011	0.333
	ConvTimeNet	0.644	0.688	0.660	0.650	1.844
	TimeNet	0.279	0.278	0.278	0.277	0.659
TATAMTRDVR	DeConFuse	0.015	0.006	0.013	0.011	0.380
	ConvTimeNet	1.153	1.213	1.161	1.153	1.219
	TimeNet	0.444	0.443	0.445	0.440	0.455
TATAPOWER	DeConFuse	0.012	0.005	0.009	0.010	0.413
	ConvTimeNet	0.435	0.442	0.431	0.452	1.265
	TimeNet	0.096	0.096	0.096	0.096	0.571
TATASTEEL	DeConFuse	0.015	0.005	0.009	0.012	0.258
	ConvTimeNet	1.363	1.390	1.369	1.365	0.862
	TimeNet	0.381	0.381	0.380	0.381	0.662

Table 5 Stock-wise forecasting results (*Continued*)

Stock name	Method	MAE close	MAE open	MAE high	MAE low	MAE NAV
TCS	DeConFuse	0.012	0.005	0.009	0.008	0.445
	ConvTimeNet	1.481	1.337	1.409	1.323	6.096
	TimeNet	0.231	0.229	0.230	0.231	0.525
TECHM	DeConFuse	0.014	0.005	0.009	0.009	0.386
	ConvTimeNet	1.857	1.634	1.753	1.746	6.126
	TimeNet	0.175	0.174	0.176	0.173	0.416
TITAN	DeConFuse	0.014	0.005	0.010	0.010	0.419
	ConvTimeNet	2.649	2.676	2.698	2.633	3.126
	TimeNet	0.548	0.548	0.547	0.548	0.630
TVSMOTOR	DeConFuse	0.014	0.005	0.009	0.011	0.385
	ConvTimeNet	1.120	1.120	1.108	1.129	0.848
	TimeNet	0.441	0.441	0.441	0.441	0.403
UBL	DeConFuse	0.018	0.008	0.014	0.013	0.418
	ConvTimeNet	0.144	0.191	0.157	0.173	0.915
	TimeNet	0.246	0.244	0.248	0.241	0.593
ULTRACEMCO	DeConFuse	0.011	0.005	0.008	0.007	0.408
	ConvTimeNet	0.088	0.086	0.086	0.088	0.712
	TimeNet	0.237	0.236	0.236	0.237	0.483
UNIONBANK	DeConFuse	0.023	0.009	0.017	0.016	0.307
	ConvTimeNet	8.195	8.076	8.034	8.207	11.330
	TimeNet	0.395	0.395	0.396	0.394	0.394
UPL	DeConFuse	0.014	0.004	0.009	0.010	0.391
	ConvTimeNet	1.182	1.034	1.122	1.101	2.592
	TimeNet	0.275	0.276	0.274	0.277	0.410
VEDL	DeConFuse	0.018	0.010	0.014	0.015	0.235
	ConvTimeNet	2.904	3.024	2.967	2.959	0.605
	TimeNet	0.295	0.295	0.295	0.295	0.720
VOLTAS	DeConFuse	0.016	0.009	0.012	0.013	0.369
	ConvTimeNet	1.244	1.272	1.268	1.254	4.493
	TimeNet	0.475	0.475	0.474	0.476	0.354
WIPRO	DeConFuse	0.009	0.005	0.007	0.007	0.456
	ConvTimeNet	0.301	0.290	0.298	0.295	0.799
	TimeNet	0.067	0.065	0.067	0.066	0.647
WOCKPHARMA	DeConFuse	0.021	0.009	0.015	0.016	0.504
	ConvTimeNet	2.407	2.486	2.335	2.582	5.903
	TimeNet	0.394	0.395	0.394	0.393	0.492
YESBANK	DeConFuse	0.014	0.006	0.01	0.011	0.335
	ConvTimeNet	0.875	0.868	0.866	0.879	1.066
	TimeNet	0.422	0.423	0.424	0.422	0.599
ZEEL	DeConFuse	0.010	0.005	0.008	0.008	0.400
	ConvTimeNet	1.132	1.135	1.136	1.123	1.449
	TimeNet	0.265	0.265	0.264	0.267	0.513

Appendix 2: Detailed stock trading results

Table 6 Stock-wise trading results

Stock name	Method	Computational model performance				Financial evaluation	
		Precision	Recall	F1 score	AUC	True AR	Predicted AR
ABIRLANUVO	DeConFuse	0.553	0.886	0.681	0.558	41.950	15.600
	ConvTimeNet	0.515	0.966	0.672	0.541		3.090
	TimeNet	0.512	0.989	0.674	0.478		8.340
ACC	DeConFuse	0.449	0.761	0.565	0.600	- 7.090	- 1.070
	ConvTimeNet	0.449	0.337	0.385	0.529		- 4.100
	TimeNet	0.389	0.152	0.219	0.506		- 9.020
ADANIENT	DeConFuse	0.581	0.962	0.724	0.560	20.690	4.570
	ConvTimeNet	0.594	0.145	0.233	0.504		69.400
	TimeNet	0.565	0.962	0.712	0.571		- 3.610
ADANIPORTS	DeConFuse	0.520	0.919	0.660	0.546	0.900	0.010
	ConvTimeNet	0.503	0.694	0.583	0.570		2.560
	TimeNet	0.534	0.568	0.550	0.559		17.750
ADANIPOWER	DeConFuse	0.461	0.862	0.601	0.492	- 34.600	10.840
	ConvTimeNet	0.473	0.569	0.517	0.460		- 28.930
	TimeNet	0.495	0.872	0.631	0.495		- 19.110
AJANTPHARM	DeConFuse	0.449	0.757	0.564	0.514	- 44.660	- 29.150
	ConvTimeNet	0.469	0.757	0.579	0.498		- 22.320
	TimeNet	0.577	0.214	0.312	0.603		- 35.460
ALBK	DeConFuse	0.485	0.776	0.597	0.550	- 23.800	- 5.890
	ConvTimeNet	0.461	0.766	0.575	0.495		- 17.440
	TimeNet	0.478	0.411	0.442	0.516		29.660
AMARAJABAT	DeConFuse	0.549	0.718	0.622	0.568	19.460	41.830
	ConvTimeNet	0.463	0.321	0.379	0.502		- 19.990
	TimeNet	0.667	0.026	0.049	0.549		- 27.870
AMBUJACEM	DeConFuse	0.486	0.829	0.613	0.576	- 8.970	- 10.080
	ConvTimeNet	0.457	0.410	0.432	0.503		- 1.310
	TimeNet	0.448	0.533	0.487	0.470		16.490
ANDHRABANK	DeConFuse	0.391	0.753	0.515	0.479	- 21.850	4.660
	ConvTimeNet	0.401	0.763	0.526	0.513		1.060
	TimeNet	0.446	0.484	0.464	0.548		- 18.610
APOLLOHOSP	DeConFuse	0.447	0.921	0.602	0.510	23.140	6.820
	ConvTimeNet	0.432	0.812	0.564	0.509		1.440
	TimeNet	0.436	0.941	0.596	0.493		4.630
APOLLOTYRE	DeConFuse	0.502	0.920	0.650	0.536	- 13.140	2.730
	ConvTimeNet	0.600	0.027	0.051	0.606		- 2.810
	TimeNet	0.482	0.973	0.645	0.468		0.950
ARVIND	DeConFuse	0.513	0.936	0.662	0.571	16.320	19.560
	ConvTimeNet	0.603	0.376	0.463	0.637		- 33.780
	TimeNet	0.476	1.000	0.645	0.445		0.000
ASHOKLEY	DeConFuse	0.532	0.849	0.654	0.520	47.650	- 16.530
	ConvTimeNet	0.524	0.092	0.157	0.502		- 14.800
	TimeNet	0.522	0.798	0.631	0.551		- 13.550
ASIANPAINT	DeConFuse	0.523	0.868	0.652	0.595	32.770	1.250
	ConvTimeNet	0.500	0.245	0.329	0.539		4.400
	TimeNet	0.463	1.000	0.633	0.487		0.000
AUROPHARMA	DeConFuse	0.511	0.835	0.634	0.532	3.370	4.430
	ConvTimeNet	0.484	0.679	0.565	0.509		- 5.900
	TimeNet	0.468	0.954	0.628	0.548		- 8.060

Table 6 Stock-wise trading results (*Continued*)

Stock name	Method	Computational model performance				Financial evaluation	
		Precision	Recall	F1 score	AUC	True AR	Predicted AR
AXISBANK	DeConFuse	0.527	0.843	0.649	0.535	3.830	26.440
	ConvTimeNet	0.503	0.643	0.565	0.485		12.060
	TimeNet	0.500	0.835	0.625	0.525		− 6.970
BAJAJ-AUTO	DeConFuse	0.491	0.776	0.601	0.552	12.590	15.430
	ConvTimeNet	0.431	0.234	0.303	0.518		− 9.380
	TimeNet	0.463	0.355	0.402	0.512		− 10.670
BAJFINANCE	DeConFuse	0.570	0.934	0.708	0.487	21.610	−4.050
	ConvTimeNet	0.526	0.440	0.479	0.441		16.480
	TimeNet	0.569	1.000	0.725	0.568		0.000
BANKBARODA	DeConFuse	0.584	0.473	0.523	0.569	− 21.990	2.880
	ConvTimeNet	0.485	0.573	0.525	0.495		− 3.680
	TimeNet	0.286	0.018	0.034	0.539		− 16.310
BANKINDIA	DeConFuse	0.463	0.925	0.617	0.428	− 29.380	− 2.880
	ConvTimeNet	0.491	0.757	0.596	0.500		− 25.090
	TimeNet	0.571	0.224	0.322	0.567		− 19.800
BATAINDIA	DeConFuse	0.523	0.693	0.596	0.494	63.650	34.340
	ConvTimeNet	0.000	0.000	0.000	0.522		0.000
	TimeNet	0.520	0.456	0.486	0.547		6.090
BEL	DeConFuse	0.457	0.892	0.604	0.592	− 17.530	− 22.310
	ConvTimeNet	0.421	0.785	0.548	0.560		− 18.020
	TimeNet	0.405	0.985	0.574	0.566		1.220
BHARATFORG	DeConFuse	0.496	1.000	0.663	0.507	− 2.210	3.800
	ConvTimeNet	0.400	0.035	0.065	0.578		− 3.510
	TimeNet	0.493	0.982	0.657	0.496		1.500
BHARTIARTL	DeConFuse	0.486	0.817	0.609	0.563	9.350	− 10.08
	ConvTimeNet	0.580	0.279	0.377	0.527		− 7.500
	TimeNet	0.493	0.327	0.393	0.535		− 7.670
BHEL	DeConFuse	0.540	0.857	0.662	0.578	− 3.050	10.340
	ConvTimeNet	0.555	0.589	0.571	0.576		− 32.780
	TimeNet	0.481	0.562	0.519	0.494		− 7.340
BIOCON	DeConFuse	0.523	0.780	0.626	0.487	30.340	− 9.750
	ConvTimeNet	1.000	0.051	0.097	0.540		11.350
	TimeNet	0.539	0.407	0.464	0.520		− 0.280
BOSCHLTD	DeConFuse	0.437	0.938	0.596	0.550	− 5.430	4.380
	ConvTimeNet	0.464	0.481	0.473	0.513		3.330
	TimeNet	0.000	0.000	0.000	0.496		0.000
BPCL	DeConFuse	0.525	0.850	0.649	0.509	− 0.640	− 0.740
	ConvTimeNet	0.535	0.611	0.570	0.561		− 2.290
	TimeNet	0.482	0.956	0.641	0.466		− 1.660
BRITANNIA	DeConFuse	0.604	0.871	0.714	0.550	17.710	4.930
	ConvTimeNet	0.558	0.258	0.353	0.492		17.400
	TimeNet	0.500	0.043	0.079	0.572		42.380
CAIRN	DeConFuse	0.558	0.682	0.614	0.540	38.310	− 14.830
	ConvTimeNet	0.833	0.059	0.110	0.483		69.850
	TimeNet	0.000	0.000	0.000	0.480		63.040
CANBK	DeConFuse	0.500	0.798	0.615	0.552	− 2.440	− 9.350
	ConvTimeNet	0.472	0.862	0.610	0.471		15.920
	TimeNet	0.485	0.908	0.633	0.528		− 20.500
CASTROLIND	DeConFuse	0.468	0.843	0.602	0.502	− 12.570	− 17.840
	ConvTimeNet	0.427	0.800	0.557	0.464		− 15.310
	TimeNet	0.800	0.057	0.107	0.516		− 20.970

Table 6 Stock-wise trading results (*Continued*)

Stock name	Method	Computational model performance				Financial evaluation	
		Precision	Recall	F1 score	AUC	True AR	Predicted AR
CEATLTD	DeConFuse	0.474	0.797	0.595	0.598	– 10.760	5.010
	ConvTimeNet	0.413	0.725	0.526	0.509		– 27.600
	TimeNet	0.434	0.957	0.597	0.520		– 10.180
CENTURYTEX	DeConFuse	0.575	0.807	0.672	0.602	– 18.430	– 21.330
	ConvTimeNet	0.513	0.675	0.583	0.535		– 16.620
	TimeNet	0.498	1.000	0.665	0.483		0.000
CESC	DeConFuse	0.489	0.789	0.604	0.562	2.300	– 4.980
	ConvTimeNet	0.550	0.101	0.171	0.535		– 5.930
	TimeNet	0.458	0.844	0.594	0.476		– 7.060
CIPLA	DeConFuse	0.472	0.810	0.596	0.564	– 3.130	– 12.260
	ConvTimeNet	0.508	0.619	0.558	0.541		– 7.370
	TimeNet	0.462	0.867	0.603	0.536		– 3.270
COALINDIA	DeConFuse	0.557	0.462	0.505	0.528	– 2.370	– 1.030
	ConvTimeNet	0.500	0.051	0.093	0.433		– 5.210
	TimeNet	0.667	0.051	0.095	0.489		6.380
COLPAL	DeConFuse	0.519	0.893	0.657	0.436	16.070	6.000
	ConvTimeNet	0.643	0.074	0.133	0.562		1.580
	TimeNet	0.566	0.355	0.437	0.524		– 3.180
DABUR	DeConFuse	0.542	0.791	0.643	0.560	21.590	– 3.260
	ConvTimeNet	0.500	0.026	0.050	0.503		41.300
	TimeNet	0.500	0.983	0.663	0.560		– 4.800
DHFL	DeConFuse	0.513	0.836	0.635	0.553	– 8.590	– 8.510
	ConvTimeNet	0.449	0.726	0.555	0.501		7.130
	TimeNet	0.456	1.000	0.627	0.547		0.000
DISHTV	DeConFuse	0.497	0.815	0.618	0.512	– 14.010	20.570
	ConvTimeNet	0.507	0.954	0.662	0.536		– 12.220
	TimeNet	0.469	0.981	0.635	0.539		0.700
DIVISLAB	DeConFuse	0.505	0.867	0.638	0.485	2.800	– 0.920
	ConvTimeNet	0.460	0.513	0.485	0.474		14.960
	TimeNet	0.489	0.973	0.651	0.567		– 4.620
DLF	DeConFuse	0.583	0.903	0.709	0.545	14.530	32.160
	ConvTimeNet	0.605	0.395	0.478	0.565		3.060
	TimeNet	0.539	0.992	0.699	0.524		2.690
DRREDDY	DeConFuse	0.518	0.870	0.649	0.586	– 2.060	10.640
	ConvTimeNet	0.492	0.774	0.601	0.470		5.080
	TimeNet	0.507	0.991	0.671	0.487		– 10.530
EICHERMOT	DeConFuse	0.515	0.936	0.664	0.519	– 7.280	– 1.070
	ConvTimeNet	0.478	0.681	0.561	0.494		– 7.780
	TimeNet	0.503	0.904	0.646	0.553		0.750
ENGINEERSIN	DeConFuse	0.568	0.659	0.610	0.612	– 3.150	– 40.820
	ConvTimeNet	0.456	0.439	0.447	0.508		– 9.830
	TimeNet	0.500	0.085	0.146	0.473		– 27.400
EXIDEIND	DeConFuse	0.525	0.850	0.649	0.603	22.020	9.570
	ConvTimeNet	0.629	0.195	0.297	0.542		2.170
	TimeNet	0.484	0.788	0.599	0.506		17.840
FEDERALBNK	DeConFuse	0.479	0.810	0.600	0.551	– 23.270	– 20.170
	ConvTimeNet	0.434	0.790	0.560	0.511		16.480
	TimeNet	0.428	0.860	0.571	0.508		– 9.940
GAIL	DeConFuse	0.554	0.683	0.612	0.496	35.420	1.670
	ConvTimeNet	0.000	0.000	0.000	0.564		0.000
	TimeNet	0.714	0.083	0.149	0.521		29.550

Table 6 Stock-wise trading results (Continued)

Stock name	Method	Computational model performance				Financial evaluation	
		Precision	Recall	F1 score	AUC	True AR	Predicted AR
GLENMARK	DeConFuse	0.543	0.847	0.662	0.546	– 12.340	7.550
	ConvTimeNet	0.640	0.483	0.551	0.580		– 14.500
	TimeNet	0.529	0.780	0.630	0.490		4.890
GMRINFRA	DeConFuse	0.512	0.792	0.622	0.547	8.230	3.520
	ConvTimeNet	0.424	0.132	0.201	0.537		46.980
	TimeNet	0.000	0.000	0.000	0.523		0.000
GODREJIND	DeConFuse	0.551	0.932	0.692	0.572	12.190	6.320
	ConvTimeNet	0.528	0.957	0.681	0.569		– 4.980
	TimeNet	0.515	1.000	0.680	0.584		1.560
GRASIM	DeConFuse	0.451	0.854	0.590	0.571	11.750	31.030
	ConvTimeNet	0.457	0.552	0.500	0.563		4.060
	TimeNet	0.421	1.000	0.590	0.563		– 0.660
HAVELLS	DeConFuse	0.562	0.886	0.688	0.534	25.080	4.960
	ConvTimeNet	0.929	0.106	0.190	0.553		1.110
	TimeNet	0.586	0.724	0.647	0.621		28.710
HCLTECH	DeConFuse	0.596	0.862	0.704	0.510	26.700	– 4.330
	ConvTimeNet	0.573	0.331	0.42	0.477		13.730
	TimeNet	0.566	0.985	0.719	0.529		1.090
HDFC	DeConFuse	0.557	0.817	0.662	0.530	– 13.020	11.470
	ConvTimeNet	0.677	0.175	0.278	0.551		7.020
	TimeNet	0.515	0.575	0.543	0.492		18.220
HDFCBANK	DeConFuse	0.551	0.851	0.669	0.561	– 0.470	9.890
	ConvTimeNet	0.569	0.306	0.398	0.510		– 7.500
	TimeNet	0.529	0.992	0.690	0.522		0.520
HDIL	DeConFuse	0.466	0.883	0.610	0.565	– 51.190	– 11.390
	ConvTimeNet	0.448	0.915	0.601	0.482		27.120
	TimeNet	0.445	1.000	0.610	0.474		0.000
HEROMOTOCO	DeConFuse	0.482	0.796	0.601	0.556	– 19.99	– 1.530
	ConvTimeNet	0.529	0.350	0.421	0.570		– 18.100
	TimeNet	0.418	0.573	0.484	0.442		– 0.910
HEXAWARE	DeConFuse	0.577	0.879	0.697	0.518	41.150	– 3.690
	ConvTimeNet	1.000	0.015	0.030	0.495		20.850
	TimeNet	0.570	0.955	0.714	0.458		5.010
HINDALCO	DeConFuse	0.495	0.872	0.631	0.547	6.020	– 6.310
	ConvTimeNet	0.474	0.679	0.558	0.524		1.110
	TimeNet	0.494	0.807	0.613	0.540		– 19.450
HINDPETRO	DeConFuse	0.459	0.931	0.615	0.507	– 18.980	– 1.200
	ConvTimeNet	0.446	0.775	0.566	0.549		– 14.200
	TimeNet	0.445	1.000	0.615	0.457		0.000
HINDUNILVR	DeConFuse	0.594	0.956	0.733	0.512	8.010	2.820
	ConvTimeNet	0.500	0.030	0.056	0.497		10.740
	TimeNet	0.623	0.696	0.657	0.578		20.200
HINDZINC	DeConFuse	0.529	0.894	0.664	0.581	– 8.970	7.870
	ConvTimeNet	0.617	0.257	0.362	0.570		– 26.230
	TimeNet	0.495	0.938	0.648	0.511		0.920
IBREALEST	DeConFuse	0.613	0.642	0.627	0.562	50.250	4.550
	ConvTimeNet	0.750	0.028	0.055	0.560		2.720
	TimeNet	0.000	0.000	0.000	0.455		0.000
IBULHSGFIN	DeConFuse	0.534	0.814	0.645	0.574	– 33.740	3.660
	ConvTimeNet	0.488	0.907	0.634	0.562		2.130
	TimeNet	0.447	0.837	0.583	0.491		4.990

Table 6 Stock-wise trading results (*Continued*)

Stock name	Method	Computational model performance				Financial evaluation	
		Precision	Recall	F1 score	AUC	True AR	Predicted AR
ICICIBANK	DeConFuse	0.514	0.664	0.580	0.554	– 15.240	– 7.840
	ConvTimeNet	0.528	0.262	0.350	0.530		7.090
	TimeNet	0.455	0.047	0.085	0.471		32.410
IDBI	DeConFuse	0.545	0.757	0.634	0.596	– 38.100	– 4.320
	ConvTimeNet	0.503	0.775	0.610	0.529		– 14.250
	TimeNet	0.577	0.505	0.538	0.538		– 11.360
IDEA	DeConFuse	0.450	0.949	0.610	0.571	– 26.870	– 12.280
	ConvTimeNet	0.415	0.667	0.512	0.549		10.310
	TimeNet	0.395	0.495	0.439	0.414		26.380
IDFC	DeConFuse	0.460	0.737	0.566	0.500	10.310	7.640
	ConvTimeNet	0.511	0.232	0.319	0.550		– 28.470
	TimeNet	0.444	0.040	0.074	0.538		– 11.310
IFCI	DeConFuse	0.541	0.653	0.592	0.612	– 21.380	– 10.090
	ConvTimeNet	0.429	0.713	0.535	0.489		9.880
	TimeNet	0.450	0.178	0.255	0.542		1.240
IGL	DeConFuse	0.505	0.955	0.660	0.545	– 17.220	– 4.580
	ConvTimeNet	0.489	1.000	0.657	0.425		0.000
	TimeNet	0.483	0.902	0.629	0.500		3.870
INDIACEM	DeConFuse	0.512	0.796	0.623	0.607	3.720	– 15.030
	ConvTimeNet	0.450	0.537	0.489	0.452		– 17.100
	TimeNet	0.473	0.907	0.622	0.541		– 1.060
INDUSINDBK	DeConFuse	0.510	0.896	0.650	0.485	2.350	– 2.270
	ConvTimeNet	0.250	0.026	0.047	0.483		7.450
	TimeNet	0.502	1.000	0.669	0.455		0.000
INFY	DeConFuse	0.590	0.803	0.677	0.519	19.370	23.970
	ConvTimeNet	0.590	0.348	0.440	0.501		23.650
	TimeNet	0.577	0.598	0.587	0.482		33.220
IOC	DeConFuse	0.546	0.848	0.664	0.560	7.260	– 8.670
	ConvTimeNet	0.495	0.938	0.648	0.527		– 1.190
	TimeNet	0.477	0.946	0.635	0.452		1.350
IRB	DeConFuse	0.528	0.920	0.671	0.567	– 14.090	– 15.820
	ConvTimeNet	0.517	0.821	0.634	0.509		– 20.420
	TimeNet	0.489	1.000	0.657	0.491		0.000
ITC	DeConFuse	0.515	0.785	0.622	0.550	16.580	8.780
	ConvTimeNet	0.482	0.383	0.427	0.509		16.990
	TimeNet	0.465	0.935	0.621	0.550		– 2.330
JINDALSTEL	DeConFuse	0.547	0.894	0.679	0.497	34.970	19.940
	ConvTimeNet	0.440	0.089	0.149	0.434		114.370
	TimeNet	0.535	0.187	0.277	0.548		35.170
JISLJALEQS	DeConFuse	0.495	0.877	0.633	0.480	– 26.510	– 9.490
	ConvTimeNet	0.495	0.412	0.450	0.521		– 6.950
	TimeNet	0.477	0.623	0.540	0.455		18.140
JPASSOCIAT	DeConFuse	0.467	0.324	0.383	0.465	– 15.680	– 7.23
	ConvTimeNet	0.545	0.056	0.101	0.503		– 22.480
	TimeNet	0.000	0.000	0.000	0.504		0.000
JSWENERGY	DeConFuse	0.537	0.784	0.637	0.573	28.740	25.080
	ConvTimeNet	0.509	0.569	0.537	0.512		– 2.810
	TimeNet	0.494	0.873	0.631	0.472		11.840
JSWSTEEL	DeConFuse	0.567	0.850	0.680	0.559	17.590	3.040
	ConvTimeNet	0.560	0.425	0.483	0.522		– 20.500
	TimeNet	0.520	0.975	0.678	0.476		– 4.980

Table 6 Stock-wise trading results (Continued)

Stock name	Method	Computational model performance				Financial evaluation	
		Precision	Recall	F1 score	AUC	True AR	Predicted AR
JUBLFOOD	DeConFuse	0.586	0.882	0.704	0.554	24.580	7.970
	ConvTimeNet	0.520	0.205	0.294	0.501		22.900
	TimeNet	0.750	0.071	0.129	0.582		110.88
JUSTDIAL	DeConFuse	0.570	0.450	0.503	0.560	29.030	1.600
	ConvTimeNet	0.643	0.248	0.358	0.560		− 20.230
	TimeNet	0.000	0.000	0.000	0.439		0.000
KOTAKBANK	DeConFuse	0.584	0.910	0.711	0.526	27.020	− 5.120
	ConvTimeNet	0.000	0.000	0.000	0.502		0.000
	TimeNet	0.579	0.955	0.721	0.511		0.900
KSCL	DeConFuse	0.545	0.838	0.660	0.572	4.420	− 15.790
	ConvTimeNet	0.535	0.575	0.554	0.545		46.130
	TimeNet	0.522	0.300	0.381	0.473		30.920
KTKBANK	DeConFuse	0.494	0.784	0.606	0.518	− 16.590	− 15.610
	ConvTimeNet	0.488	0.532	0.509	0.530		− 6.400
	TimeNet	0.491	0.730	0.587	0.545		− 13.540
L&TFH	DeConFuse	0.468	0.906	0.617	0.550	− 20.710	− 7.570
	ConvTimeNet	0.453	0.906	0.604	0.550		− 19.540
	TimeNet	0.432	0.958	0.595	0.478		− 1.020
LICHSGFIN	DeConFuse	0.517	0.852	0.640	0.549	− 21.250	12.680
	ConvTimeNet	0.471	0.676	0.555	0.514		14.560
	TimeNet	0.476	0.980	0.640	0.530		− 1.150
LT	DeConFuse	0.525	0.810	0.637	0.524	7.670	− 3.420
	ConvTimeNet	0.562	0.078	0.136	0.553		− 1.190
	TimeNet	0.519	0.241	0.329	0.534		21.790
LUPIN	DeConFuse	0.562	0.860	0.680	0.545	− 46.000	− 13.900
	ConvTimeNet	0.534	0.645	0.584	0.504		− 9.170
	TimeNet	0.518	0.702	0.596	0.515		− 13.000
M&M	DeConFuse	0.576	0.760	0.656	0.556	26.670	− 5.130
	ConvTimeNet	1.000	0.062	0.117	0.550		9.230
	TimeNet	0.596	0.791	0.680	0.570		5.390
M&MFIN	DeConFuse	0.505	0.819	0.625	0.435	57.200	3.640
	ConvTimeNet	0.000	0.000	0.000	0.539		0.000
	TimeNet	0.590	0.310	0.407	0.519		26.820
MARUTI	DeConFuse	0.527	0.883	0.660	0.574	10.200	3.950
	ConvTimeNet	0.508	0.559	0.532	0.562		6.680
	TimeNet	0.485	1.000	0.653	0.500		0.000
MINDTREE	DeConFuse	0.521	0.718	0.604	0.483	51.140	34.170
	ConvTimeNet	0.625	0.097	0.168	0.528		1.180
	TimeNet	0.577	0.291	0.387	0.498		37.020
MOTHERSUMI	DeConFuse	0.510	0.863	0.641	0.504	− 0.320	4.730
	ConvTimeNet	0.510	0.537	0.526	0.519		− 22.050
	TimeNet	0.489	0.979	0.653	0.535		2.480
MRF	DeConFuse	0.489	0.571	0.527	0.463	− 3.020	2.370
	ConvTimeNet	0.500	0.089	0.152	0.520		− 6.320
	TimeNet	0.482	0.964	0.643	0.480		− 3.050
NHPC	DeConFuse	0.531	0.520	0.526	0.598	− 10.570	− 3.130
	ConvTimeNet	0.556	0.255	0.350	0.564		13.660
	TimeNet	0.000	0.000	0.000	0.474		0.000
NMDC	DeConFuse	0.550	0.783	0.646	0.557	− 10.800	5.560
	ConvTimeNet	0.540	0.558	0.549	0.528		− 16.940
	TimeNet	0.528	0.633	0.576	0.500		− 10.610

Table 6 Stock-wise trading results (*Continued*)

Stock name	Method	Computational model performance				Financial evaluation	
		Precision	Recall	F1 score	AUC	True AR	Predicted AR
NTPC	DeConFuse	0.487	0.862	0.623	0.480	1.690	− 4.410
	ConvTimeNet	0.535	0.349	0.422	0.560		− 7.440
	TimeNet	0.497	0.789	0.610	0.534		3.830
OFSS	DeConFuse	0.500	0.723	0.591	0.453	21.390	33.070
	ConvTimeNet	0.593	0.134	0.219	0.518		6.100
	TimeNet	0.667	0.017	0.033	0.419		6.190
OIL	DeConFuse	0.533	0.731	0.616	0.525	− 21.220	− 15.240
	ConvTimeNet	0.495	0.577	0.533	0.541		− 17.520
	TimeNet	0.496	0.769	0.603	0.465		− 13.470
ONGC	DeConFuse	0.526	0.750	0.618	0.604	20.320	13.740
	ConvTimeNet	0.496	0.519	0.507	0.498		− 13.270
	TimeNet	0.447	0.704	0.547	0.543		11.750
ORIENTBANK	DeConFuse	0.466	0.880	0.609	0.553	− 10.110	− 17.560
	ConvTimeNet	0.435	0.740	0.548	0.492		16.580
	TimeNet	0.430	0.490	0.458	0.518		38.720
PAGEIND	DeConFuse	0.503	0.935	0.655	0.489	39.910	8.130
	ConvTimeNet	0.375	0.195	0.256	0.400		0.630
	TimeNet	0.447	0.545	0.491	0.521		1.050
PETRONET	DeConFuse	0.520	0.929	0.669	0.525	12.330	− 9.760
	ConvTimeNet	0.520	0.241	0.331	0.539		− 12.190
	TimeNet	0.485	0.982	0.649	0.546		1.450
PFC	DeConFuse	0.503	0.733	0.597	0.532	2.150	7.310
	ConvTimeNet	0.479	0.657	0.554	0.551		11.310
	TimeNet	0.458	0.667	0.543	0.497		− 14.680
PIDILITIND	DeConFuse	0.602	0.773	0.677	0.596	30.150	11.440
	ConvTimeNet	0.564	0.500	0.530	0.501		12.880
	TimeNet	0.550	1.000	0.710	0.518		0.000
PNB	DeConFuse	0.512	0.644	0.570	0.572	− 23.580	− 14.500
	ConvTimeNet	0.496	0.634	0.557	0.560		− 18.650
	TimeNet	0.495	0.455	0.474	0.550		− 6.780
POWERGRID	DeConFuse	0.491	0.757	0.595	0.560	10.340	− 5.810
	ConvTimeNet	0.473	0.777	0.588	0.531		− 6.230
	TimeNet	0.481	0.495	0.488	0.511		0.420
PTC	DeConFuse	0.526	0.766	0.624	0.610	− 19.080	− 30.920
	ConvTimeNet	0.471	0.607	0.531	0.518		− 34.44
	TimeNet	0.449	0.907	0.601	0.537		− 5.060
RCOM	DeConFuse	0.474	0.540	0.505	0.524	− 29.600	− 38.130
	ConvTimeNet	0.091	0.010	0.018	0.489		− 39.190
	TimeNet	0.000	0.000	0.000	0.495		0.000
RECLTD	DeConFuse	0.439	0.863	0.582	0.511	− 29.540	− 32.010
	ConvTimeNet	0.407	0.621	0.492	0.491		− 2.110
	TimeNet	0.420	0.495	0.454	0.500		− 25.420
RELCAPITAL	DeConFuse	0.497	0.843	0.625	0.575	− 31.650	12.140
	ConvTimeNet	0.481	0.704	0.571	0.563		− 14.590
	TimeNet	0.471	0.981	0.637	0.491		− 15.740
RELIANCE	DeConFuse	0.588	0.870	0.702	0.574	4.780	9.430
	ConvTimeNet	0.000	0.000	0.000	0.524		0.000
	TimeNet	0.571	0.802	0.667	0.506		4.880
RELINFRA	DeConFuse	0.535	0.868	0.662	0.528	− 12.910	− 11.870
	ConvTimeNet	0.493	0.930	0.644	0.505		− 3.650
	TimeNet	0.493	0.974	0.655	0.482		1.860

Table 6 Stock-wise trading results (Continued)

Stock name	Method	Computational model performance				Financial evaluation	
		Precision	Recall	F1 score	AUC	True AR	Predicted AR
RPOWER	DeConFuse	0.541	0.860	0.660	0.588	– 40.030	2.300
	ConvTimeNet	0.512	0.947	0.660	0.605		9.490
	TimeNet	0.500	0.904	0.644	0.529		– 15.860
SAIL	DeConFuse	0.541	0.748	0.628	0.498	10.540	41.720
	ConvTimeNet	0.576	0.276	0.374	0.498		12.370
	TimeNet	0.562	0.146	0.232	0.482		11.190
SBIN	DeConFuse	0.518	0.673	0.585	0.569	– 1.370	– 3.740
	ConvTimeNet	0.491	0.486	0.488	0.545		6.730
	TimeNet	0.463	0.467	0.465	0.484		29.460
SIEMENS	DeConFuse	0.520	0.919	0.664	0.574	– 6.930	3.220
	ConvTimeNet	0.540	0.613	0.574	0.559		8.280
	TimeNet	0.485	0.991	0.651	0.505		– 1.080
SOUTHBANK	DeConFuse	0.492	0.492	0.492	0.628	– 34.640	– 42.640
	ConvTimeNet	0.407	0.559	0.471	0.542		– 48.180
	TimeNet	0.000	0.000	0.000	0.568		0.000
SRF	DeConFuse	0.543	0.809	0.649	0.569	– 15.350	42.110
	ConvTimeNet	0.471	0.205	0.286	0.484		– 37.280
	TimeNet	0.479	0.859	0.615	0.487		– 19.230
SRTRANSFIN	DeConFuse	0.575	0.780	0.662	0.564	2.810	32.140
	ConvTimeNet	0.765	0.106	0.186	0.578		– 0.030
	TimeNet	0.517	0.862	0.646	0.441		9.070
STAR	DeConFuse	0.474	0.881	0.617	0.581	–38.200	– 34.590
	ConvTimeNet	0.453	0.631	0.527	0.531		– 50.680
	TimeNet	0.462	0.512	0.486	0.482		– 56.200
SUNPHARMA	DeConFuse	0.476	0.908	0.625	0.521	24.640	– 0.220
	ConvTimeNet	0.468	0.743	0.574	0.472		15.310
	TimeNet	0.476	0.734	0.578	0.520		–15.150
SUNTV	DeConFuse	0.502	0.928	0.652	0.513	– 9.190	– 7.630
	ConvTimeNet	0.588	0.423	0.492	0.600		– 16.630
	TimeNet	0.485	0.892	0.629	0.533		– 6.620
SYNDIBANK	DeConFuse	0.450	0.786	0.572	0.552	– 52.140	– 9.720
	ConvTimeNet	0.443	0.755	0.558	0.540		–17.660
	TimeNet	0.222	0.020	0.037	0.533		–34.330
TATACHEM	DeConFuse	0.538	0.739	0.620	0.565	8.710	8.700
	ConvTimeNet	0.700	0.061	0.112	0.504		3.210
	TimeNet	0.530	0.765	0.620	0.548		2.060
TATACOMM	DeConFuse	0.516	0.855	0.644	0.581	2.020	– 9.330
	ConvTimeNet	0.488	0.936	0.642	0.537		– 14.430
	TimeNet	0.480	0.964	0.640	0.562		– 4.480
TATAGLOBAL	DeConFuse	0.573	0.850	0.685	0.574	29.440	14.710
	ConvTimeNet	0.530	0.733	0.615	0.564		– 6.740
	TimeNet	0.536	0.850	0.660	0.534		– 9.600
TATAMOTORS	DeConFuse	0.522	0.761	0.619	0.576	– 30.220	– 1.920
	ConvTimeNet	0.483	0.633	0.548	0.511		– 6.140
	TimeNet	0.450	0.450	0.450	0.491		– 2.090
TATAMTRDVR	DeConFuse	0.478	0.854	0.610	0.518	– 35.66	– 1.030
	ConvTimeNet	0.447	0.738	0.557	0.502		– 17.550
	TimeNet	0.455	0.971	0.610	0.502		– 8.180
TATAPOWER	DeConFuse	0.540	0.514	0.527	0.564	– 4.090	– 17.580
	ConvTimeNet	0.558	0.276	0.369	0.549		– 25.530
	TimeNet	0.333	0.010	0.019	0.450		– 8.550

Table 6 Stock-wise trading results (*Continued*)

Stock name	Method	Computational model performance				Financial evaluation	
		Precision	Recall	F1 score	AUC	True AR	Predicted AR
TATASTEEL	DeConFuse	0.552	0.807	0.655	0.528	17.240	− 10.030
	ConvTimeNet	0.562	0.613	0.586	0.551		− 22.210
	TimeNet	0.518	0.958	0.673	0.474		− 13.700
TCS	DeConFuse	0.573	0.746	0.648	0.557	33.910	2.550
	ConvTimeNet	0.636	0.056	0.102	0.453		2.990
	TimeNet	0.573	0.714	0.636	0.565		6.360
TECHM	DeConFuse	0.555	0.835	0.667	0.480	49.080	29.110
	ConvTimeNet	0.578	0.496	0.534	0.507		47.820
	TimeNet	0.572	0.685	0.624	0.563		− 5.130
TITAN	DeConFuse	0.562	0.744	0.641	0.562	18.960	4.930
	ConvTimeNet	0.000	0.000	0.000	0.560		0.000
	TimeNet	0.528	0.628	0.574	0.477		24.260
TVSMOTOR	DeConFuse	0.453	0.953	0.614	0.504	− 4.950	− 11.570
	ConvTimeNet	0.431	0.802	0.561	0.438		− 19.260
	TimeNet	0.441	1.000	0.612	0.473		0.000
UBL	DeConFuse	0.609	0.664	0.635	0.550	59.870	32.690
	ConvTimeNet	1.000	0.049	0.094	0.568		17.720
	TimeNet	0.600	0.221	0.323	0.515		47.160
ULTRACEMCO	DeConFuse	0.569	0.757	0.649	0.585	26.850	− 0.390
	ConvTimeNet	0.556	0.522	0.538	0.581		− 16.410
	TimeNet	0.500	0.991	0.665	0.542		0.860
UNIONBANK	DeConFuse	0.497	0.689	0.577	0.553	− 4.350	30.000
	ConvTimeNet	0.453	0.709	0.553	0.494		− 25.830
	TimeNet	0.408	0.194	0.263	0.511		− 34.140
UPL	DeConFuse	0.480	0.897	0.627	0.553	5.600	2.450
	ConvTimeNet	0.480	0.738	0.585	0.526		5.010
	TimeNet	0.459	0.841	0.594	0.501		− 3.330
VEDL	DeConFuse	0.475	0.864	0.613	0.599	3.610	− 4.550
	ConvTimeNet	0.433	0.636	0.515	0.570		− 28.800
	TimeNet	0.360	0.136	0.198	0.491		− 18.810
VOLTAS	DeConFuse	0.497	0.864	0.631	0.483	60.280	8.460
	ConvTimeNet	1.000	0.009	0.018	0.541		4.970
	TimeNet	0.480	1.000	0.649	0.528		0.000
WIPRO	DeConFuse	0.503	0.780	0.612	0.535	− 11.360	3.560
	ConvTimeNet	0.532	0.615	0.570	0.562		− 13.570
	TimeNet	0.492	0.872	0.629	0.575		8.590
WOCKPHARMA	DeConFuse	0.516	0.899	0.656	0.559	− 7.170	18.620
	ConvTimeNet	0.523	0.517	0.520	0.515		59.110
	TimeNet	0.487	0.865	0.623	0.524		− 2.650
YESBANK	DeConFuse	0.522	0.828	0.640	0.565	0.050	3.180
	ConvTimeNet	0.494	0.664	0.566	0.523		− 7.690
	TimeNet	0.507	1.000	0.672	0.559		0.000
ZEEL	DeConFuse	0.557	0.900	0.688	0.535	4.660	− 8.240
	ConvTimeNet	0.607	0.375	0.464	0.622		− 6.830
	TimeNet	0.527	0.900	0.667	0.569		12.100

Abbreviations

TL: Transform learning; CTL: Convolutional transform learning; CNN: Convolutional neural network; LSTM: Long short-term memory; GRU: Gated recurrent unit; ReLU: Rectified linear unit; SELU: Scaled exponential linear units; NSE : National Stock Exchange; AUC: Area under curve; ROC: Receiver operating characteristics; NAV: Net asset value; RDF: Random decision forest; EEG: Electroencephalogram; ECG: Electrocardiogram; AR: Annualized returns; MAE: Mean absolute error

Authors' contributions

Ms. Pooja Gupta has introduced the CTL within the fusion framework and performed all the numerical experiments. Ms. Jyoti Maggu originally formulated the transform learning model and the deep version for it. Dr. Angshul Majumdar has helped with the model formulation and the assessment of the experimental part. Dr. Emilie Chouzenoux and Dr. Giovanni Chierchia have contributed in the formulation of the model and the optimization algorithms. All the authors have contributed to the writing and proofreading of the paper. The authors read and approved the final manuscript.

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Availability of data and materials

The dataset used is a real dataset of the Indian National Stock Exchange (NSE) of past 4 years and is publicly available. We have shared the data with our implementation available at <https://github.com/pooja290992/DeConFuse.git>.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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