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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 Axios[1], 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 DeepMind[2].

In this work, we would like to keep the best of both worlds, i.e., the success of convolutive 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 $\left(s^{(k)}\right)_{1\leq k\leq K}$

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

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

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

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

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

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

where $T = \begin{bmatrix} t_1 & \ldots & t_M \end{bmatrix}$, $S = \begin{bmatrix} s^{(1)} & \ldots & s^{(K)} \end{bmatrix}^\top$, and $X = \begin{bmatrix} x_1^{(k)} & \ldots & x_M^{(k)} \end{bmatrix}_{1\leq k\leq K}$. The cost function in problem (2) can be compactly rewritten as[3]

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

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 $\varphi : \mathcal{H} \to]-\infty, +\infty]$ as

$$\operatorname{prox}_\varphi(\tilde{x}) = \underset{x\in\mathcal{H}}{\arg\min}\, \varphi(x) + \frac{1}{2}\left\|x - \tilde{x}\right\|^2. \tag{5}$$

Then, the alternating proximal algorithm reads

$$\begin{array}{l} \text{For } n = 0, 1, \ldots \\ \left\lfloor \begin{array}{l} T^{[n+1]} = \operatorname{prox}_{\gamma_1 F(\cdot, X^{[n]})}\left(T^{[n]}\right) \\ X^{[n+1]} = \operatorname{prox}_{\gamma_2 F(T^{[n+1]},\cdot)}\left(X^{[n]}\right) \end{array}\right. \end{array} \tag{6}$$

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 DeConFuse[4] strategy.

[3]Note 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.
[4]Code available at: https://github.com/pooja290992/DeConFuse.git

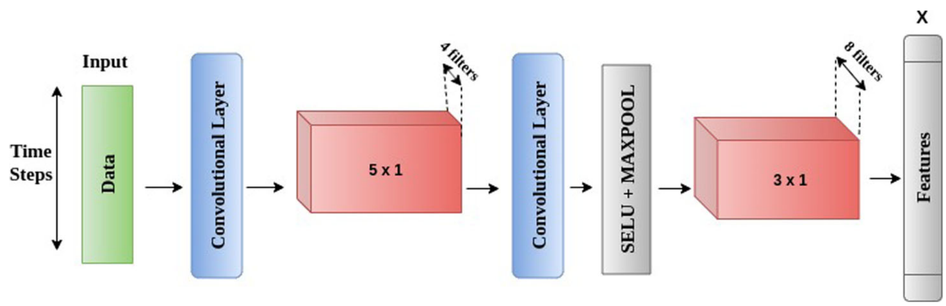


Fig. 1 Deep CTL architecture. The illustration is given for $L = 2$ layers, with the first layer T_1 composed of $M_1 = 4$ filters of size 5×1, and the second layer composed of $M_2 = 8$ filters of size 3×1

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 $\widehat{X}$ to the CTL problem, assuming fixed filters T, can be reformulated as the simple application of an element-wise activation function, that is

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

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

$$(\forall \ell \in \{1, \ldots, L-1\}) \qquad X_\ell = \phi_\ell(T_\ell * X_{\ell-1}), \tag{8}$$

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

Putting all together, deep CTL amounts to

$$\underset{T_1,\ldots,T_L,X}{\text{minimize}} \quad F_{\text{conv}}(T_1, \ldots, T_L, X \mid S) \tag{9}$$

where

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

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 $c \in \{1, \ldots, C\}$, we learn a different set of convolutional filters $T_1^{(c)}, \ldots, T_L^{(c)}$ and features $X^{(c)}$. At the same time, we learn the

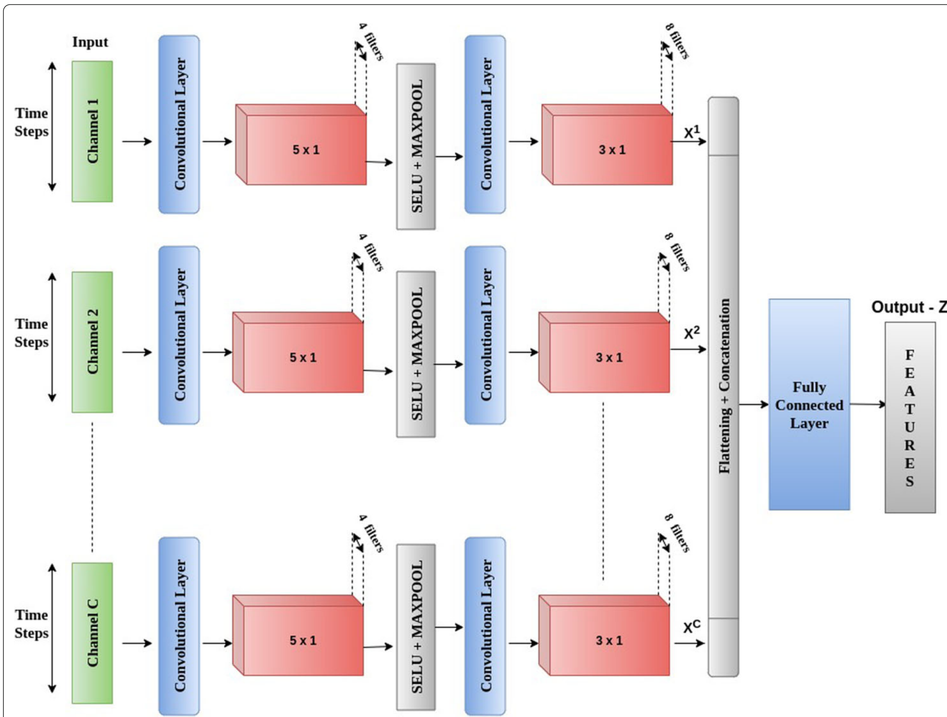


Fig. 2 DeConFuse architecture

(not convolutional) linear transform $\widetilde{T} = (\widetilde{T}_c)_{1 \le c \le C}$ to fuse the channel-wise features $X = (X^{(c)})_{1 \le c \le C}$, 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

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

where

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

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 $\widetilde{T}$ 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 $\widetilde{T}$ 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

$$
\text{For } n = 0, 1, \ldots
\left\lfloor
\begin{aligned}
T^{[n+1]} &= T^{[n]} - \gamma \nabla_T J(T^{[n]}, X^{[n]}, \widetilde{T}^{[n]}, Z^{[n]}) \\
X^{[n+1]} &= \mathcal{P}_+ \left(X^{[n]} - \gamma \nabla_X J(T^{[n]}, X^{[n]}, \widetilde{T}^{[n]}, Z^{[n]}) \right) \\
\widetilde{T}^{[n+1]} &= \widetilde{T}^{[n]} - \gamma \nabla_{\widetilde{T}} J(T^{[n]}, X^{[n]}, \widetilde{T}^{[n]}, Z^{[n]}) \\
Z^{[n+1]} &= \mathcal{P}_+ \left(Z^{[n]} - \gamma \nabla_Z J(T^{[n]}, X^{[n]}, \widetilde{T}^{[n]}, Z^{[n]}) \right)
\end{aligned}
\right.
\tag{13}
$$

with initialization $T^{[0]}, X^{[0]}, \widetilde{T}^{[0]}, Z^{[0]}$, $\gamma > 0$, 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 $\widetilde{T}_c$. 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	$\mathcal{O}(I^2C^2)$	$S^{(c)} \in \mathbb{R}^{K\times D}$
	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	$\mathcal{O}(I^2C^2)$	$\text{flat}(X^{(c)}) \in \mathbb{R}^{K\times I}$
	5. log-det on conv. layers	$\mathcal{O}(P_\ell^2 M_\ell C)$	$\widetilde{T}_c \in \mathbb{R}^{I\times O}$
	6. log-det on f.-c. layer	$\mathcal{O}(I^3C^2)$	
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
$O = \alpha IC$ (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 × { **layer1** : **1D Conv**(1, 4, 5, 1, 2)[1] **Maxpool**(2, 2)[2] **SELU** **layer2** : **1D Conv**(5, 8, 3, 1, 1)[1] } **layer3** : **Fully connected**	Learning rate = 0.001, $\lambda = 0.01, \mu = 0.0001$, **Optimizer used**: **Adam** **with parameters** $(\beta1, \beta2) = (0.9, 0.999)$, weight_decay = 5e-5, epsilon = 1e-8
ConvTimeNet	5× { **layer1** : **1D Convolution**(1, 32, 9, 1, 4)[1] **Batch normalization + SELU** **layer2** : **1D Convolution**(32, 32, 3, 1, 1)[1] **Batch normalization + SELU + SC**[3] **layer3** : **1D Convolution**(32, 64, 9, 1, 4)[1] **Batch normalization + SELU** **layer4** : **1D Convolution**(64, 64, 3, 1, 1)[1] **Batch normalization + SELU + SC**[3] **layer3** : **Global Average Pooling** } **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** $(\beta1, \beta2) = (0.9, 0.999)$, weight_decay = 1e-4, epsilon = 1e-8
TimeNet	5 × { **layer1** : **LSTM unit**(1, 12, 2, *True*)[4] **layer2** : **Global Average Pooling** } **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** $(\beta1, \beta2) = (0.9, 0.999)$, 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.

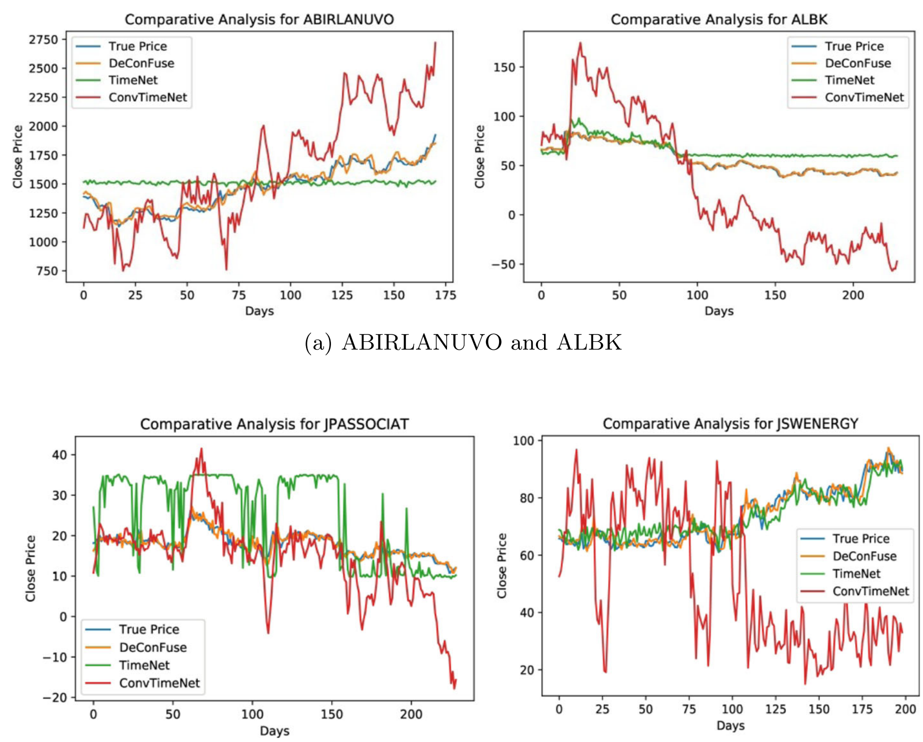
From the summary Table 3, it can be observed that our error is more than an order of magnitude better than the state of the arts. The plots for one of the regressed prices (close price) for some examples of stocks in Fig. 3 show that the predicted close prices from DeConFuse are closer to the true close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



(a) ABIRLANUVO and ALBK

(b) JPASSOCIAT and JSWENERGY

Fig. 3 Stock forecasting performance

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

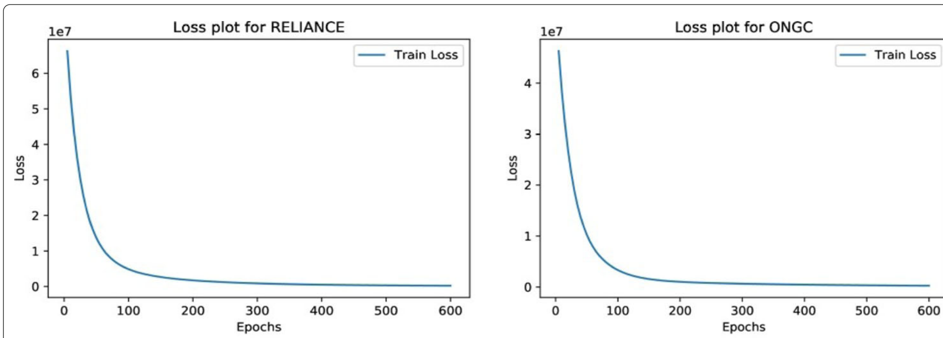
We also display empirical convergence plots for few stocks, namely RELIANCE, ONGC, HINDUNILVR, and ICICIBANK, in Fig. 4. We can see that the training loss decreases to a point of stability for each example.

5 Conclusion

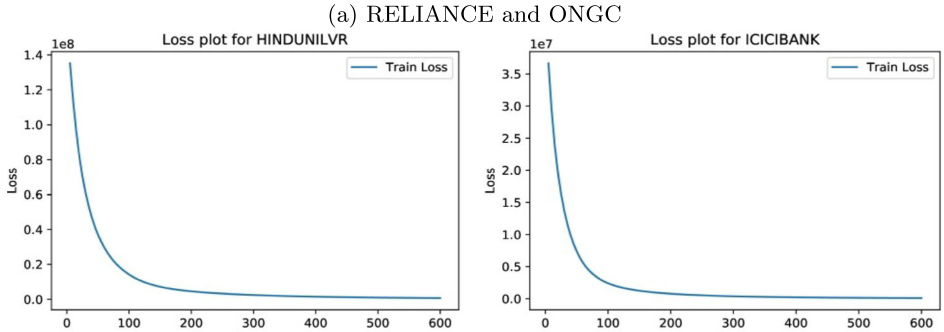
In this work, we propose DeConFuse, a deep fusion end-to-end framework for the processing of 1D multi-channel data. Unlike other deep learning models, our framework is unsupervised. It is based on a novel deep version of our recently proposed convolutional transform learning model. We have applied the 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.



(a) RELIANCE and ONGC



(b) HINDUNILVR and ICICIBANK

Fig. 4 Empirical convergence plots

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
ADANIPORTS	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
ADANIPOWER	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
AJANTPHARM	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
ALBK	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
AMARAJABAT	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**
AMBUJACEM	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
ANDHRABANK	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
APOLLOHOSP	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**
APOLLOTYRE	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**
ARVIND	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
ASHOKLEY	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
ASIANPAINT	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
AUROPHARMA	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
ENGINERSIN	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
ENGINERSIN	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.

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Not applicable.

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Competing interests
The authors declare that they have no competing interests.

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