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RESEARCH ARTICLE

Classification and Analysis of Employee Feedback with Deep Learning Algorithms

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ABSTRACT
This study aims to enhance organizational processes and support decision-making for managers by conducting an automated analysis of employee feedback through text classification of Turkish sentences. Employee satisfaction and motivation are critical factors that directly impact sustainability and efficiency goals. To overcome the challenges of manual feedback analysis, the study employs Temporal Convolutional Network (TCN), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Bidirectional Encoder Representations from Transformers (BERT) algorithms. The dataset comprises feedback collected from meeting notes, internal surveys, and manager-employee interviews, with data synthesis and preprocessing steps including text cleaning, tokenization, and modelling. The study's findings reveal that the CNN algorithm achieved the best performance, with an accuracy of 99.12%, a test loss of 6.09%, precision of 99.12%, recall of 99.12%, and an F1 score of 99.11%. This research demonstrates the valuable contribution of automated classification models in effectively and efficiently analysing employee feedback.

Keywords: Employee Feedback Classification, TCN, CNN, LSTM, BERT, Deep Learning for Text Analysis

1. Introduction

Employee satisfaction and motivation are fundamental to organizational success in today's business world. Effectively analyzing feedback from employees not only guides leadership processes but also informs organizations' strategic planning efforts. In processing large-scale datasets, machine learning and deep learning techniques accelerate the analysis process and provide cost advantages. Text classification algorithms play a crucial role by categorizing feedback into meaningful groups, thereby establishing decision-support mechanisms and contributing to developing innovative organizational strategies.

Text classification methods have broad applications, including customer relationship management, healthcare, education, law, and marketing. Examples such as categorizing customer complaints, classifying patient records, analyzing student feedback, organizing legal documents, and examining social media data highlight the functionality of this technology. Supported by artificial intelligence and deep learning methods, text classification technologies automate the transformation of unstructured data into actionable information, making processes more efficient and effective. Consequently, they serve as a critical tool in strategic decision-making processes.

The main purpose of this study is to contribute to organizational decision-making processes by analyzing employee feedback consisting of Turkish sentences. The ultimate objectives include deriving meaningful insights from feedback to enhance employee satisfaction, motivation, and engagement, transforming these insights into actionable information, and improving organizational efficiency. In the modern business world, such approaches, which serve the principles of transparency, rapid decision-making, and continuous improvement, play a strategic role in transforming business processes.

2. Literature Review

In literature, several machine learning methods have been employed for text classification. In the study by Kayakuş et al., 10,500 news articles collected from five news websites in Turkey were categorized into three classes: world, sports, and economy, using Naive Bayes and decision tree methods. Naive Bayes demonstrated better performance with an accuracy of 88.66% [1]. Bozkurt et al. classified Amazon food reviews using Random Forest (RF), CatBoost, and XGBoost algorithms, where RF achieved the highest performance with an accuracy of 90.22% [2]. Tuna et al. proposed a model for determining

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target categories for Turkish texts, showing that the FastText model delivered the best performance in identifying target terms [3]. In their study on IMDB movie reviews, Öğe et al. found that Logistic Regression and SVM algorithms performed well when combined with the Word2Vec method [4]. In another study by Metin et al., human activity classification was conducted using gyroscope and accelerometer data, achieving 97% and 99% accuracy with TSA and ESA methods, respectively. The study also introduced a new dataset and software tools for human activity classification [5]. Aydemir et al. categorized Turkish news articles into eight distinct categories, where the RF algorithm achieved the best performance with an accuracy of 99.86% [6]. Akgümüş et al. demonstrated that the Multinomial Naive Bayes model achieved a 99% accuracy rate and effectively classified customer complaints in the banking sector [7].

Literature has increasingly utilized deep learning methods for text classification in recent years. In the study by Ertem et al., LSTM and feature selection techniques were used to detect COVID-19 vaccine opposition with an accuracy of 99.23%. Data imbalance was addressed using the SMOTE method and TF-IDF [8]. Demirbilek et al. conducted sentiment analysis on Google reviews of a university in Central Anatolia using LSTM and machine learning methods, where Amazon Comprehend demonstrated the best performance across all metrics [9]. Çataltaş et al. analyzed Turkish COVID-19 tweets, showing that a CNN-LSTM model achieved 76% and 84% accuracy for sentiment classification [10]. Güler et al. examined Turkish news articles and e-commerce reviews, where their KSA-based deep learning model achieved accuracies of 91.7% and 95.6%, respectively [11]. Yılmaz et al. classified 28,104 requests in a help desk system, achieving 97.60% accuracy with the LSTM model [12]. Budak et al. found that deep-learning methods performed better in analyzing airline reviews before and after COVID-19 [13]. In their study, Sel et al. employed BERT, LSTM, and CNN models to predict gender from Turkish Twitter posts, with BERT achieving the highest accuracy of 80.1% [14]. Acı et al. used Word2Vec and KSA methods for Turkish news articles, demonstrating that KSA provided 93.3% higher accuracy than classical methods [15]. Bişkin's study applied TCN to forecast COVID-19 cases in European countries, showing that TCN outperformed LSTM and GRU models in terms of lower computation time and higher prediction accuracy [16]. Kasapbaşı et al. aimed to convert Turkish Sign Language (TİD) gestures into text using CNN-based deep learning models, achieving a high accuracy of 98% [17]. Erol et al. conducted sales forecasting using models such as CNN, LSTM, and GRU, concluding that LSTM and its variants performed best, particularly on datasets with seasonality and trends [18]. Tuna et al. demonstrated that the DeepCusComp-1 model achieved 85.83% accuracy in classifying customer complaints, outperforming other methods [19]. Aydın's study compared LSTM and BERT-based models, revealing that BERT outperformed LSTM [20]. Arslan et al. showed the success of BERT-based models in stance detection using social media data [21]. Gür compared CNN, LSTM, and GRU models, finding that a hybrid CNN-LSTM-GRU model achieved the lowest error rates and the best R^2 values [22]. Demirbilek et al. compared AWS Comprehend with deep learning methods, noting that AWS Comprehend achieved the highest performance across all metrics [23]. Kahraman et al. identified BERT as an effective tool for classifying patent texts [24]. Aydın et al. found that BERT-based models were more efficient than LSTM models in processing time and accuracy [25]. Sel et al. highlighted that BERT achieved high accuracy even on short and unstructured texts, performing well in gender prediction through Twitter-based analyses [26].

This study was conducted to address several significant gaps in literature. First, while most existing research focuses on customer feedback or social media data, there is a limited number of studies analyzing organizational internal data, particularly employee feedback. Given the critical importance of intrinsic factors such as employee satisfaction and productivity for organizations, addressing this gap is essential. Second, while literature often focuses on the performance of a single model, this study provides a comparative analysis of different algorithms, including TCN, CNN, LSTM, and BERT, thereby highlighting the effectiveness of hybrid approaches. Lastly, although preprocessing steps such as data cleaning and tokenization receive limited emphasis in literature, this study thoroughly examines the impact of these steps, aiming to bridge gaps in Natural Language Processing (NLP). In this context, the study provides a valuable contribution to supporting decision-making processes in organizational settings.

3. Background Work

TCN, CNN, LSTM, and BERT are foundational architectures in modern deep learning. While TCN and LSTM excel in time series analysis, CNN dominates image processing, and BERT performs well in NLP tasks. These models extract data features through unique mechanisms, effectively solving complex problems. Notably, BERT stands out in NLP with its bidirectional context understanding, TCN and LSTM effectively model temporal dependencies, and CNN efficiently captures visual features.

TCN is a model designed to process time series data and learn long-term dependencies efficiently and hierarchically. Through 1D convolutional layers, pooling, and normalization processes, TCN captures temporal information. Its encoder-decoder architecture generates and expands compressed representations. TCN is recognized for its faster training than RNNs and LSTMs [27]. With its convolutional layers, pooling, and Rectified Linear Unit (ReLU) activation functions, CNN is prominent in image processing. The convolutional layers extract local features, while pooling reduces dimensionality and prevents overfitting. This structure performs highly in object detection, segmentation, and image classification tasks [28]. LSTM relies on cells equipped with input, forget, and output gates to selectively control information. The cell state retains critical information and addresses the vanishing gradient problem. This architecture is widely used in NLP, speech recognition, and time series forecasting due to its ability to learn both short- and long-term dependencies [29]. BERT is an NLP model with bidirectional context understanding based on the Encoder portion of Transformer architecture. It learns contextual relationships through tasks such as Masked Language Modeling (MLM) and Next Sentence Prediction (NSP). The Classification Token (CLS) and Separator Token (SEP) tokens are particularly effective for classification and sentence relationship tasks. With fine-tuning, BERT excels in sentiment analysis, question answering, and natural language understanding tasks [30].

4. Methodology

The flow chart in Figure 1 depicts the methodology we used in this study. It involves dataset construction, data preprocessing, construction of deep learning models, and training and evaluation using cross-validation. All these steps are elaborated in the following subsections.

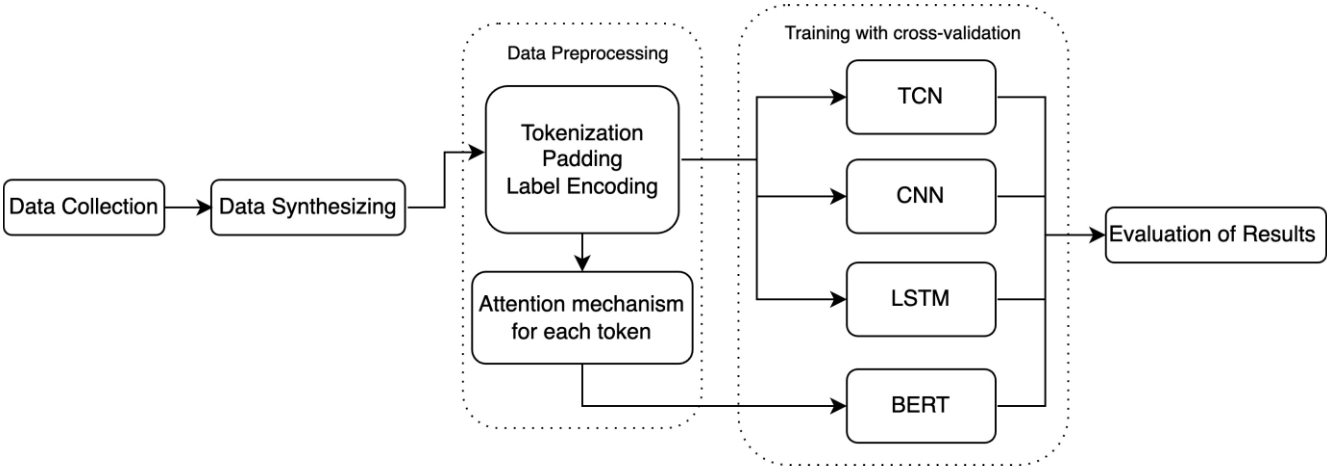


Figure 1. Methodology of the study

4.1 Dataset

The 386 Turkish sentences obtained from meeting notes, internal surveys, and manager-employee discussions in a private company in Turkey were analyzed, identifying 14 categories. All sentences were anonymized and matched with the relevant categories. Since more data was needed for model training, the existing dataset was used to teach ChatGPT the sentence-category matching process. Subsequently, 500 synthetic Turkish sentences were generated for each category, resulting in 7,000 sentences. The length of these synthetic sentences was designed to be a maximum of 17 words, with an average of 11 words. The identified categories are based on common types of employee feedback regarding work processes, and each category was assigned a label number. Table 1 presents the categories in the dataset along with example sentences.

Table 1. Real and synthetic sentences by categories

Label No	Category	Data Count	Real Sentence	Synthetic Sentence
1	Lack of Information	500	İş birimleri her talep açışında nasıl açılacağını soruyor. (Business units ask how to open requests every time they need to.)	Yöneticilerden gerekli detayları zamanında alamadığımız için projelerimiz aksıyor. (Projects are delayed because we cannot get the necessary details from managers on time.)
2	Work Environment	500	Campus gerçekten güzel. Yeni ofise beğenerek gidiyorum. (The campus is truly beautiful. I enjoy going to the new office.)	Çalışma alanlarının yetersizliği ekip içinde verimliliği olumsuz etkiliyor. (The lack of adequate workspaces negatively impacts team productivity.)
3	Change and Planning Management	500	IT tarafında hala ekipler arası iletişimin veya etkileşimin az olduğunu, birlikte çalışma ortamları için yeni planlamalar bekliyoruz. (We expect new plans to create collaborative environments as there is still	Planlamalar önceden paylaşılınca işler daha hızlı ilerliyor. (When plans are shared in advance, work progresses faster.)

			limited interaction between IT teams.)	
4	Training	500	İş biriminine ne zaman yeterli eğitim verilecek akış süreci için (When will sufficient training be provided to the business unit for the workflow process?)	Eğitimlerin yetersiz olması, çalışanların gelişimini olumsuz etkiliyor. (Insufficient training negatively affects employee development.)
5	Team Harmony	500	Ekip içi iletişim şahane herkes yardımsever. İyi ki bu ekibin bir parçasıyım. (Team communication is fantastic; everyone is helpful. I'm glad to be part of this team.)	Düzenli ekip toplantıları, iş birliğini artırıyor. (Regular team meetings enhance collaboration.)
6	Event Needs	500	Bir gün birlikte bir yerde çalışma yapsak. Gelsin hackathon. (Can we have a day of collaborative work somewhere? Let's organize a hackathon.)	Şirket piknikleri, çalışanların iş dışında da bağ kurmasını sağlar. (Company picnics help employees build bonds outside of work.)
7	Job Descriptions and Responsibilities	500	İş biriminin hiç bir şey söylemeden acil işleri kendileri yapmaları, sonra da ben bunu yapamadım IT bana yardım etsin deyip gece gündüz demeden aramaları hoş değil. Bu iş planlı olmalı herkes ona göre plan yapmalı. (The business unit takes over urgent tasks without informing anyone and later requests IT's help, which disrupts planning.)	Belirgin görev tanımları, çalışanların iş memnuniyetini artırır. (Clear job descriptions increase employee satisfaction.)
8	Welcome Kit	500	İşe başlamada hoşgeldin kiti olmaması üzücü. (It's disappointing not to have a welcome kit upon starting work.)	Hoşgeldin kitinin özenle hazırlanmış olması, yeni çalışanlara değer verildiğini hissettiriyor. (A thoughtfully prepared welcome kit makes new employees feel valued.)
9	Personal Requests	500	Personel avansı yada kredi için aksiyon alınmalı bir çok bankada olan bir süreç bizde neden yok. (Actions should be taken for employee advances or loans. Why don't we have this process like other banks?)	Yıllık izin günlerimizin arttırılmasını isterim. (I would like the number of annual leave days to be increased.)
10	Approval Processes	500	Paket oluşturma onaylar vs çok zaman alıyor ve yıpratıyor. (Package creation and approvals take too much time and are exhausting.)	Onay süreçlerinin dijitalleştirilmesi, zaman kazandırabilir. (Digitizing approval processes can save time.)
11	Staffing Shortages	500	İş birimleri kendi kaynak eksikliklerini IT deki kişileri kendi kaynakları gibi kullanarak çözmeye çalışıyorlar. (Business units try to address their staffing shortages by treating IT staff as their own resources.)	Personel eksikliği yüzünden zamanında sonuç alınamıyor. (Staffing shortages prevent timely results.)
12	Health Insurance	500	Sağlık sigortasının aileyi kapsayacak şekilde olmaması çok üzücü (It's disappointing that health insurance doesn't cover families.)	Çalışanlar için daha kapsamlı sağlık sigortası sunulmalı. (More comprehensive health insurance should be offered to employees.)

13	Salaries and Benefits	500	Zamlar çok yetersizdi, piyasanın altında kalmaya başladık. (The rises were insufficient; we're starting to fall behind the market.)	Çalışanlar için emeklilik fonları gibi yan haklar artırılmalıdır. (Benefits like retirement funds should be increased for employees.)
14	Efficient Work	500	Debug işini analistler de yapabilmeli. (Analysts should also be able to handle debugging tasks.)	Verimli çalışabilmek için iş yükü dengeli bir şekilde dağıtılmalıdır. (To work efficiently, workloads should be distributed evenly.)

4.2 Data Pre-processing

Similar preprocessing steps were applied for processing text data in TCN, CNN, and LSTM models. The texts were converted into numerical sequences using a tokenizer and padded to a fixed length of 17 using pad sequences. This ensured consistency by allowing the models to process input data of uniform length. Additionally, the categorical labels of the texts were encoded into numerical values using Label Encoder. These common preprocessing steps enabled the models to classify text data accurately. In contrast, the data preparation process for the BERT model differed from the other models. The texts were tokenized using Bert Tokenizer, padded to a fixed length 17, and subjected to truncation. Furthermore, an attention mask was created for each token. These steps facilitated BERT's ability to understand the text more accurately and effectively.

4.3 Model Training and Parameter Tuning

During the training process for TCN, CNN, LSTM, and BERT models, a stratified k-fold cross-validation method was applied, with the data validated across five folds. This approach enhanced the models' generalization capabilities and contributed to obtaining more consistent results. Additionally, the TCN, CNN, and LSTM models used categorical cross-entropy as the loss function, while the Adam optimizer was employed for optimization across all models.

Table 2. Parameter values used in models

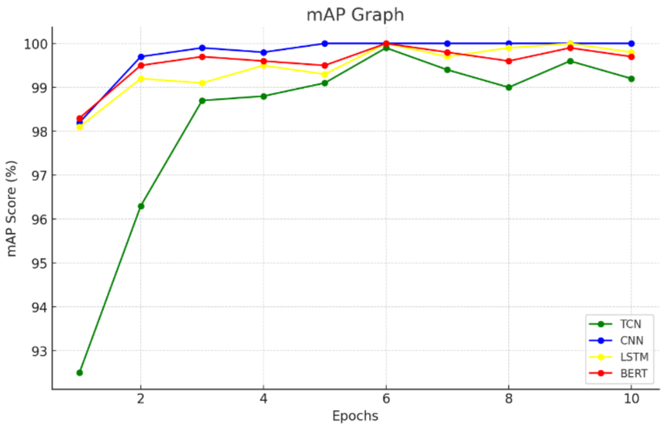
Parameter	**TCN**	**CNN**	**LSTM**	**BERT**
Embedding Dimension	128	128	128	128
Conv1D Filters (1st Layer)	64	128	-	-
Conv1D Filters (2nd Layer)	128	-	-	-
Kernel Size	3	3	-	-
Dropout Rate (1st Layer)	0.2	0.2	0.3	-
Dropout Rate (2nd Layer)	0.3	0.3	0.3	0.3
Dense Layer Units	128	128	128	-
Padding Sequences Max	17	17	17	17
Optimizer	Adam	Adam	Adam	Adam
Learning Rate	0.001	0.001	0.001	0.001
Loss Function	categorical_ crossentropy	categorical_ crossentropy	categorical_ crossentropy	CrossEntropyLoss
Batch Size	32	32	32	32
Epochs	10	10	10	10
Validation Splits	Stratified	Stratified	Stratified	-
Cross Validation Folds	5	5	5	5
Max Pooling Size	-	2	-	-
LSTM Units	-	-	128	-
Tokenizer	-	-		BertTokenizer (bert-base-uncased)
Pretrained Model	-	-		bert-base-uncased
Dropout Rate	-	-	-	0.3

The TCN model offered an architecture optimized for multi-class classification problems and was trained using the categorical cross-entropy loss function. Similarly, the CNN model followed a comparable training process but focused on extracting spatial features. In contrast, the LSTM model employed a specialized training process tailored for time-series data and sequential information. These three models generally shared similar loss functions and optimization methods during training.

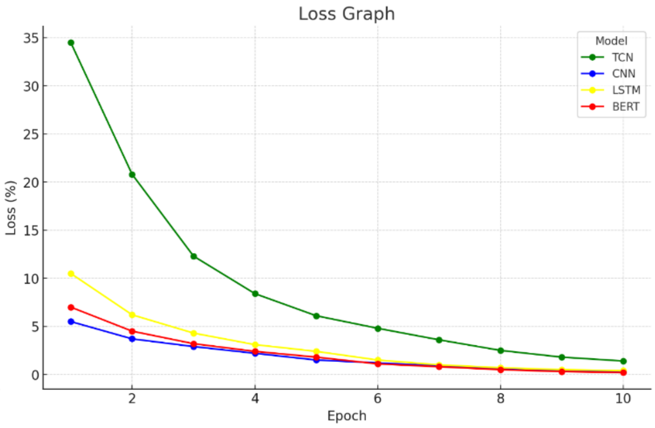
Unlike the other models, BERT is a pre-trained language model, and therefore, smaller learning rates were used during its training. The cross-entropy loss function was employed for BERT, which is designed to optimize contextual language understanding. The operations performed on the models are outlined in Figure 1. All models were developed using Google Colab platform. The parameter configurations used in the models, determined based on the dataset size, are presented in Table 2.

4.4 Performance Evaluation

The performance of the models was evaluated using various metrics such as accuracy, precision, recall, and F1 score. Accuracy represents the proportion of correctly classified examples to the total number of examples. Precision and recall, respectively, indicate how accurately the model predicts a specific class and how effectively it identifies the actual instances of that class. The F1 score, as a balanced measure of precision and recall, comprehensively evaluates the model's classification performance. Test loss measures the model's performance on test data, where a lower loss indicates better generalizability. During the training of all models, 5-fold cross-validation was applied, and the values presented in the tables and matrices were calculated as averages across these folds. Additionally, during the model training process, the average loss and accuracy values for each epoch were calculated and presented as graphs in Figure 2. After training all models, the resulting performance metrics are presented in Table 3.



a)



b)

Figure 2. Performance graphics of the models (a) mAP (b) Loss

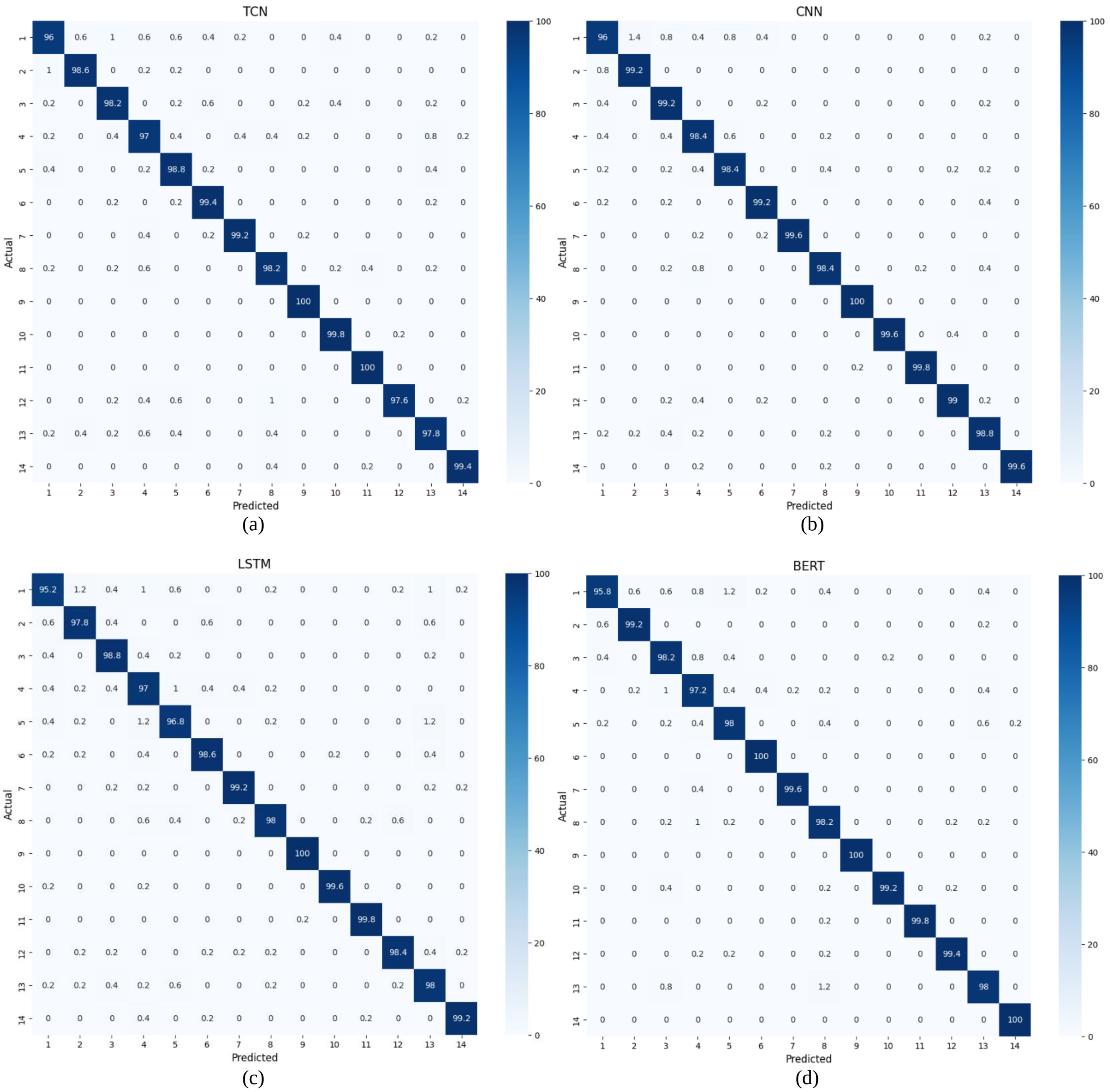
Table 3. Performance values of the models

Performance Metrics	TCN	CNN	LSTM	BERT
Test Loss (%)	33.79	6.09	10.55	6.35
Test Accuracy (%)	93.12	99.12	98.06	98.64
Precision (%)	90.78	99.12	98.11	98.69
Recall (%)	90.79	99.12	98.06	98.64
F1 Score (%)	90.68	99.11	98.06	98.64
Average Training Duration (sn)	100.63	185.16	646.39	418.59

According to the results in Table 3, the CNN model achieved the lowest test loss value of 6.09%, indicating a high generalization capability. BERT demonstrated a similar performance with a test loss of 6.35%. In contrast, the TCN model lagged with a test loss of 33.79%. Regarding accuracy, the CNN model attained the highest value at 99.12%, followed by BERT (98.64%) and LSTM (98.06%), showcasing strong performance. TCN ranked the lowest with an accuracy of 93.12%. For precision and recall metrics, CNN achieved the highest values, at 99.12%, followed by BERT and LSTM. When considering the F1 score, a balanced measure of precision and recall, CNN again led with 99.11%, with BERT (98.64%) and LSTM (98.06%) closely trailing. Regarding training time, TCN was the fastest, completing training in only 100.63 seconds. Although CNN required a longer training time of 185.16 seconds, it compensated for this with its superior accuracy. On the other hand, LSTM and BERT required significantly more resources, with training times of 646.39 seconds and 418.59 seconds, respectively. The average confusion matrices for the 5-fold cross-validation results for all four models are shown separately in Figure 3.

5. Conclusions

In this study, employee feedback data was classified using four different deep-learning models, and the models' performances and training times were compared. The CNN model emerged as the most successful, achieving the best results across all performance metrics, including test loss, accuracy, precision, recall, and F1 score. With its high accuracy, CNN proved an effective option for classification tasks. The BERT model, known for its ability to learn contextual language representations, demonstrated performance close to that of CNN. However, its longer training times made it more computationally expensive. The TCN model stood out with its fast-training time but fell behind the other models in performance metrics. While TCN offers advantages for time-series analysis, it did not deliver strong performance in the classification task of this study. Despite its ability to process sequential data, the LSTM model lagged behind CNN due to its longer training time and lower accuracy.



(a) (b) (c) (d)

Figure 3. Confusion Matrices (a) TCN, (b) CNN, (c) LSTM, (d) BERT

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Conflict of Interest Notice
The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical Approval and Informed Consent
It is declared that during the preparation process of this study, scientific and ethical principles were followed, and all the studies benefited from are stated in the bibliography.

Availability of data and material
Employee Feedback Dataset can be obtained at https://www.kaggle.com/datasets/gokhanyigidefe/personel-geri-bildirimleri-veriseti

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