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Artificial Intelligence-Based Automation of the Referral Process for Applications Submitted to CİMER

CİMER'e Yapılan Başvuruların Sevk Sürecinin Yapay Zekâ Destekli Otomasyonu

Araştırma Makalesi / Research Article

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ABSTRACT

In recent years, technological advancements have significantly increased the volume of data stored and processed. While this growth presents many advantages, it also brings challenges, such as the need for effective text classification. In Türkiye, the Presidency's Communication Centre (CİMER) was established to promote principles of good governance, such as accountability, transparency, the rule of law, and citizen participation. CİMER is an effective channel through which citizens can obtain redress for administrative actions, and the number of applications submitted has been increasing annually. As the number of citizen applications submitted to CİMER increases each year, addressing each application within the legally mandated timeframe has become increasingly demanding. In this context, handling all procedures related to the referral of CİMER applications within an automated system is very important. In addition, the manual referral of applications to the relevant public institutions places a considerable burden on human resources. This study introduces a novel approach using artificial intelligence to automate the referral process of CİMER applications. It proposes a system in which applications submitted to CİMER are classified by a pre-trained artificial intelligence model operating in the background of the CİMER system. Based on the classification results, applications are either automatically forwarded to the relevant ministry or sent to the CİMER application pool for manual referral. The study compares two deep learning methods for text classification—Convolutional Neural Networks (CNN) and BERT. The anal-

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yses show that the BERT model outperforms CNN, achieving a validation accuracy of 99.986% and a test accuracy of 99.924%.

Keywords: Presidency's Communication Centre, governance, automation, savings on public resources, artificial intelligence

Öz

Son yıllarda meydana gelen birçok teknolojik gelişmeyle beraber, saklanan ve işlenen veri miktarında ciddi bir artış meydana gelmiştir. Bu artış, birçok faydanın yanı sıra metinlerin sınıflandırılması gibi bazı problemleri de beraberinde getirmiştir. Hesap verebilirlik, saydamlık, hukukun üstünlüğü ve katılımın önde tutulması ilkelerinin tamamını içerisine alan bir çatı olarak ortaya çıkan iyi yönetişim anlayışına uyum sağlanabilmesi adına Türkiye'de Cumhurbaşkanlığı İletişim Merkezi (CİMER) kurulmuştur. İdarenin eylemlerine karşı vatandaşlara etkin ve hızlı bir hak arama yöntemi sağlayan CİMER'e yapılan başvurular her yıl artmaktadır. Bu başvuruların yasal süreleri içerisinde cevaplandırılması gerektiğinden dolayı, başvuruların ilgili kamu kuruluşlarına gönderilmesi ve en kısa sürede cevaplanması, gecikme halinde ilgililerin uyarılması işlemlerinin bir otomasyon sistemi içerisinde gerçekleştirilebilmesi oldukça önemlidir. CİMER başvuru havuzuna gelen başvuruların kurum personeli tarafından ilgili kamu kurumuna elle sevk edilmesi CİMER'e yapılan başvuru sayısının sürekli artmasından dolayı önemli ölçüde insan kaynağı gerektirmektedir. Bu çalışmada, CİMER sistemine gelen başvuruların sevk sürecinin yapay zekâ yöntemleri ile otomasyonu için daha önce yapılmamış olan yenilikçi bir yaklaşım önerilmiştir. Bu yaklaşım, vatandaşların CİMER başvuru havuzuna yönlendirmek istediği başvuruların CİMER sisteminin arka planında çalışan önceden eğitilmiş yapay zekâ modeli ile sınıflandırılması ve yapılan bu sınıflandırmanın sonucuna göre başvurunun ilgili bakanlığa otomatik olarak sevk edilmesi yahut elle sevk edilmek üzere CİMER başvuru havuzuna yönlendirilmesi şeklindedir. Bu çalışmada, metin sınıflandırması için iki farklı derin öğrenme metodu kıyaslanmış, bu yöntemlerden en verimli olanı tespit edilmiştir. Yapılan analizler neticesinde, evrişimsel sinir ağı modeline ilişkin doğrulama doğruluğu değeri %99.336, test doğruluğu değeri %98.223 ve BERT modeline ilişkin doğrulama doğruluğu değeri %99.986, test doğruluğu değeri ise %99.924 olarak bulunmuştur. Elde edilen bu sonuçlar neticesinde, BERT modelinin evrişimsel sinir ağı modeline kıyasla daha verimli olduğu tespit edilmiştir.

Anahtar Kelimeler: Cumhurbaşkanlığı İletişim Merkezi, yönetişim, otomasyon, kamu kaynaklarından tasarruf, yapay zekâ

Introduction

Today, with the widespread use of computers, optical readers, the internet and advanced information storage technologies, there has been a significant increase in the amount of data produced, stored and processed (Pilavcılar, 2007). This increase has brought about the need to analyse and process data, which in today's world cannot be performed without computers most of the time (Pilavcılar, 2007). Today, the increasing amount of text data used in a wide variety of fields has created the need for automatic categorisation of this data for different purposes. Text classification (TC) has become an important field to meet this requirement (Aytekin et al., 2018, pp. 782–792).

TC is considered a sub-branch of a large field called text mining (TM) (Aytekin et al., 2018, pp. 782–792). TM is the process of extracting previously unknown information from text data in an unstructured format and has gained great popularity since the 2000s (Pilavcılar, 2007). TC aims to determine which of the predetermined categories a particular text belongs to by looking at its features. TC is used in many areas (Figure 1). Although it has developed in some areas, the need for TC is increasing in every environment where large amounts of text data are present (Aytekin et al., 2018, pp. 782–792).

Figure 1. Application areas of TC

Most of the research in the area of TC has generally focused on English or languages with similar structures to English (Pilavcılar, 2007). In these languages, the number of suffixes added to words is low, and therefore, TC operations become simpler. However, in inflecting languages such as Turkish, words take suffixes to form meaningful units, and this makes the processing of the language more complex. Therefore, studies on Turkish text classification are more limited compared to studies on English text classification (Pilavcılar, 2007). In this context, the problem of Turkish text classification is addressed in this study.

The main purpose of existence of states is to provide basic services such as security, shelter, health, education, etc. to their citizens (Şahin, 2018, pp. 99–139). While the relationship between the state and citizens was quite simple in classical periods, the protection of rights and freedoms also came to the fore in the modern understanding of the state (Gündüz & Artar, 2023, pp. 660–700; Şahin, 2018, pp. 99–139). For this purpose, states today adopt an administrative approach that is accountable, transparent, based on the rule of law and encourages participation. This understanding has been reinforced by the concept of good governance (Şahin, 2018, pp. 99–139; Yağmurlu & Eroğlu, 2020, pp. 139–167).

The world has become a big village under the influence of globalisation, which reveals that the state system and administration must be updated with more heterogeneous tools. It is a fact that modern societies require innovation and transformation in the face of political, social, economic and technological changes (Gündüz & Artar, 2023, pp. 660–700). Important reforms have been made in the field of public administration in order to adapt to these changes (Güler, 2020, pp. 273–287; Şahin, 2018, pp. 99–139). In Türkiye, especially after the 2000s, the CİMER, which is an important part of these innovations and governance understanding, has been established (Güler, 2020, pp. 273–287; Gündüz & Artar, 2023, pp. 660–700). CİMER is an important platform that enables citizens to submit applications to the administration. Citizens can submit their applications, such as suggestions, complaints and information, through this platform (Acar, 2018, pp. 4836–4848; Eski et al., 2019, pp 163-182; Göksu & Avcı, 2025, pp. 163-196; Güllüpunar, 2022, pp. 310-332; Gündüz & Artar, 2023, pp. 660–700; Kayıkçı & Tatar, 2021, pp. 873-898; Saylam, 2020, pp. 23–37; Yağmurlu & Eroğlu, 2020, pp. 139–167). While the communication between the state and citizens is improved through CİMER, the effectiveness of public administration is also increased (Karaca Belli et al., 2022, pp. 64-80; Selvi et al., 2019, pp. 13-37). For all these reasons, synthetic CİMER applications were used as the data set for the Turkish TC problem considered in this study.

The number of applications submitted to the CİMER system is increasing annually, and it is crucial to classify these applications accurately. Forwarding CİMER applications to the relevant institution correctly plays a critical role in preventing loss of time (Özgür et al., 2019, pp. 13–37). These applications must be answered within 15 working days within the scope of the right to information and within 30 days within the scope of the right to petition. This means that application processes must be managed more quickly and efficiently. This situation reveals the importance of time savings that can be achieved by increasing the efficiency of the automation system for the referral process of CİMER applications. For all these reasons, synthetic data was generated to be suitable for the applications forwarded to the CİMER automation system within the scope of this study.

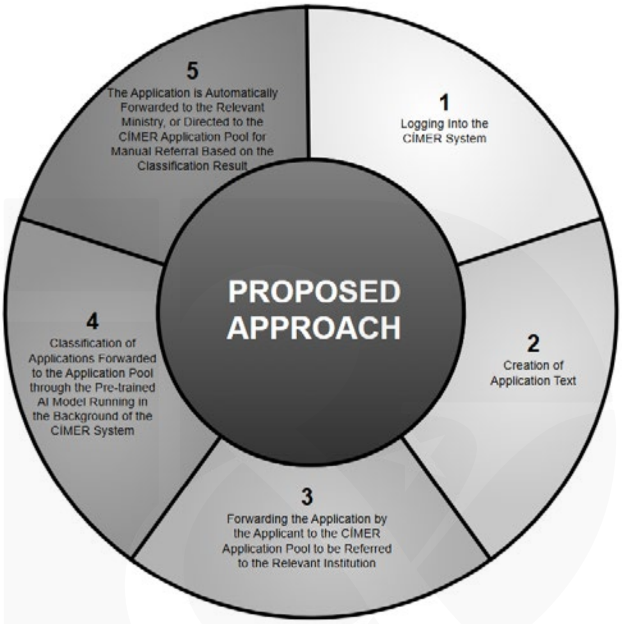
In this study, AI techniques were used to classify the applications. AI is a rapidly developing technology that is widely used in many practical applications (Goodfellow et al., 2016). One of the important benefits of AI is that it can increase accuracy by reducing errors. In addition, AI systems can analyse a large amount of data in real time and provide valuable information. Natural language processing (NLP) is one of the important sub-fields of AI and includes techniques that can be used in areas where text data is dense (Taşar et al., 2021; Yılmaz & Yumuşak, 2021, pp. 81–85). NLP is a method that includes both morphological and semantic analysis of text and has gained great popularity in recent years (Yılmaz & Yumuşak, 2021, pp. 81–85). TC is an important application area of NLP, and accurate classification of texts is provided by machines (Aytekin et al., 2018, pp. 782–792; Şahin & Diri, 2021; Erkırtay & Ünal, 2021, pp. 168–185). The use of machine learning (ML) and deep learning (DL) methods in TM is increasing day by day (Şeker et al., 2017, pp. 47–64; Erkırtay & Ünal, 2021, pp. 168–185). For all these reasons, DL techniques were used in TC within the scope of this study.

Convolutional neural networks (CNNs) have been one of the most commonly used deep learning (DL) models in TC (Sel & Hanbay, 2021, pp. 675–684). Today, CNNs can classify objects with an accuracy rate far above human performance (Ertam, 2019; Özdemir & Türkoğlu, 2022, pp. 517–529). According to the literature review, it can be seen that CNNs are used in many studies in the TC field (Acı and Çırak, 2019, pp. 219–228; Alparslan & Dursun, 2023, pp. 21–31; Dorukbaşı, 2023; Şeker et al., 2017, pp. 47–64). For all these reasons, considering the literature review, CNN was used as the DL model in this study. When the literature is reviewed, it is seen that the BERT model is also widely used in many studies in the MS field (Arzu & Aydoğan, 2023, pp. 1–6; Çelikten & Bulut, 2021; Güven, 2023, pp. 1–6; Helli et al., 2023; Koçak & Yiğit, 2023, pp. 277–285; Özkan & Kar, 2022, pp. 504–519; Sel & Hanbay, 2021, pp. 675–684; Taşar et al., 2021). BERT, which stands for “Bidirectional Encoder Representations of Transformers”, is a transformer-based DL architecture that can be used to tackle various NLP tasks (Koçak & Yiğit, 2023, pp. 277–285; Özkan & Kar, 2022, pp. 504–519; Tuncer et al., 2021, pp. 243–252). Transformer-based TC has recently been a widely studied subject in the NLP and DL fields (Arzu & Aydoğan, 2023, pp. 1–6). The BERT model has produced high accuracy results in many studies in the TC field (Çelikten & Bulut, 2021; Dorukbaşı, 2023; Güven, 2023, pp. 1–6). For all these reasons, the BERT model was used as another DL model in this study. Despite its many advantages, the BERT model is computationally expensive and requires substantial graphics processing unit (GPU) resources for training. Therefore, instead of training the BERT model from scratch, fine-tuning was performed on a pre-trained BERT model used in this study (Koçak & Yiğit, 2023, pp. 277–285). Due to the reasons mentioned above and the lower computational cost of CNNs, this study compared the fine-tuned BERT model with the CNN model trained from scratch to determine a cost-efficient AI model that achieves the highest accuracy.

DL methods such as CNNs and BERT models are among the most commonly used methods in the field of TC (Ertam, 2019; Sel & Hanbay, 2021, pp. 675–684). CNNs are powerful models that can classify textual data with high accuracy (Ertam, 2019; Özdemir & Türkoğlu, 2022, pp. 517–529). In addition, the BERT model is also a highly successful model in NLP tasks (Koçak & Yiğit, 2023, pp. 277–285; Özkan & Kar, 2022, pp. 504–519).

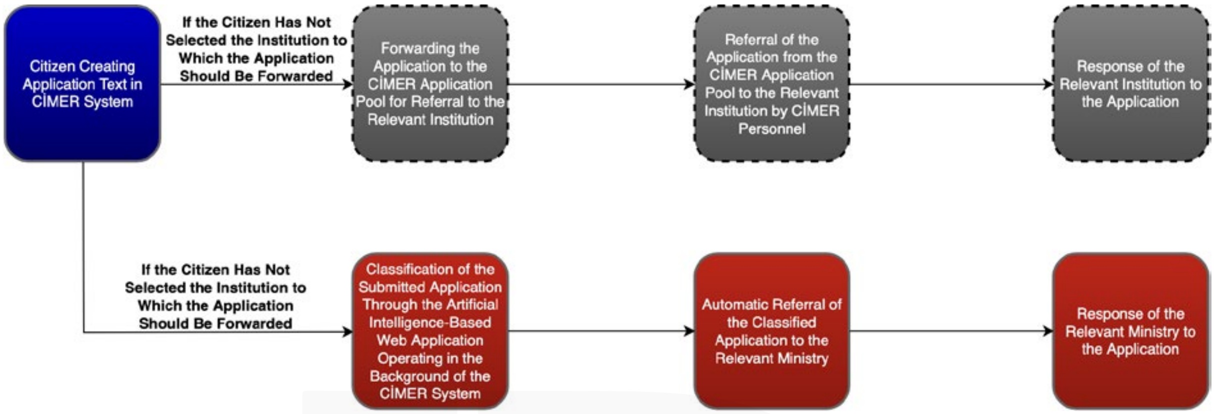
Therefore, in this study, CNN and BERT models were used to classify CİMER applications. In particular, a pre-trained BERT model was fine-tuned to reduce the computational cost (Koçak & Yiğit, 2023, pp. 277–285). The aim of this study is to determine the most efficient and economical AI model and to integrate it into the CİMER system to classify applications. Within the scope of this study, an AI-based approach is proposed for the automatic classification of applications made to the CİMER system (Figure 2).

Figure 2. Flow chart for the processes of the proposed approach



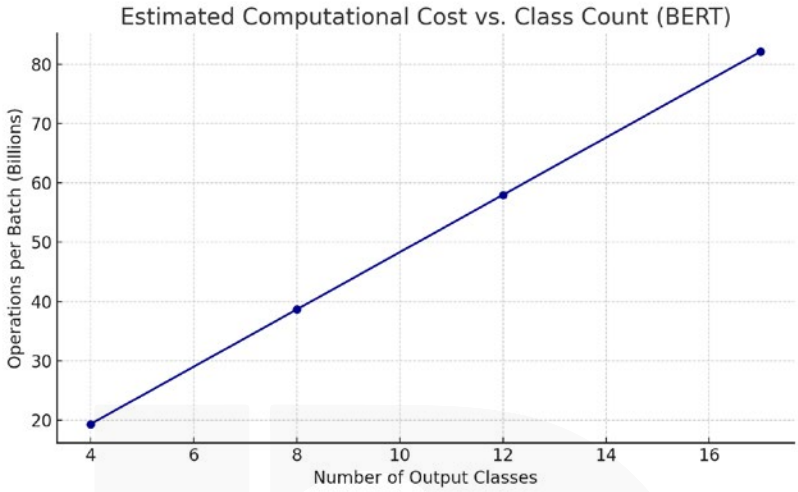
The proposed approach aims to automatically forward applications directed to the CİMER application pool to the relevant institution, thereby accelerating management processes. This method will ensure more efficient use of public resources, prevent loss of time, and enable citizens to receive services faster. The integration of the proposed approach into the existing CİMER system is depicted in Figure 3. The blue box in this figure represents the step shared by both the existing CİMER system and the proposed approach. The grey boxes represent the steps currently carried out in the existing CİMER system, and the red boxes represent the new processes to be integrated into the CİMER system with the adaptation of the proposed approach. As illustrated in Figure 3, the proposed approach enables the automation of the referral process, which is currently carried out manually by CİMER personnel, using AI techniques, thereby eliminating the need for human intervention.

Figure 3. Flow chart illustrating the integration of the proposed AI-based approach into the CİMER system



The BERT model is based on the transformer architecture. In transformer-based architectures, each encoder layer consists of two main components: the multi-head self-attention mechanism and a position-wise feed-forward neural network. In particular, the self-attention mechanism computes attention matrices by modelling interactions among all tokens in the input sequence. The computational complexity of this process is proportional to the square of the number of tokens in the input sequence multiplied by the hidden size (dimensionality of the hidden layer) of the model (Lou et al., 2020). Since BERT typically has a multi-layered structure, this operation is repeated across all layers during training. Thus, the overall computational complexity becomes proportional to the product of the batch size, the number of transformer layers, the square of the input token length, and the hidden size (Lou et al., 2020). Repeating this computation across layers results in a significant memory and computational costs, especially for long input sequences and deep models. For example, assuming a batch size of 8 and considering the BERT-base architecture with 12 layers, a maximum sequence length of 512 tokens, and a hidden size of 768, the estimated computational complexity is 8*12*5122*768 = 19,33*109 operations. In BERT-based classification models, the Softmax activation function is commonly used in the output layer. In this function, each additional class increases the computational cost linearly (Rawat et al., 2020). Based on this information and the example computation above, the graph in Figure 4 presents the estimated computational cost for different numbers of output classes ranging from 4 to 17.

Figure 4. Estimated computational cost plot for the BERT model as a function of output class count

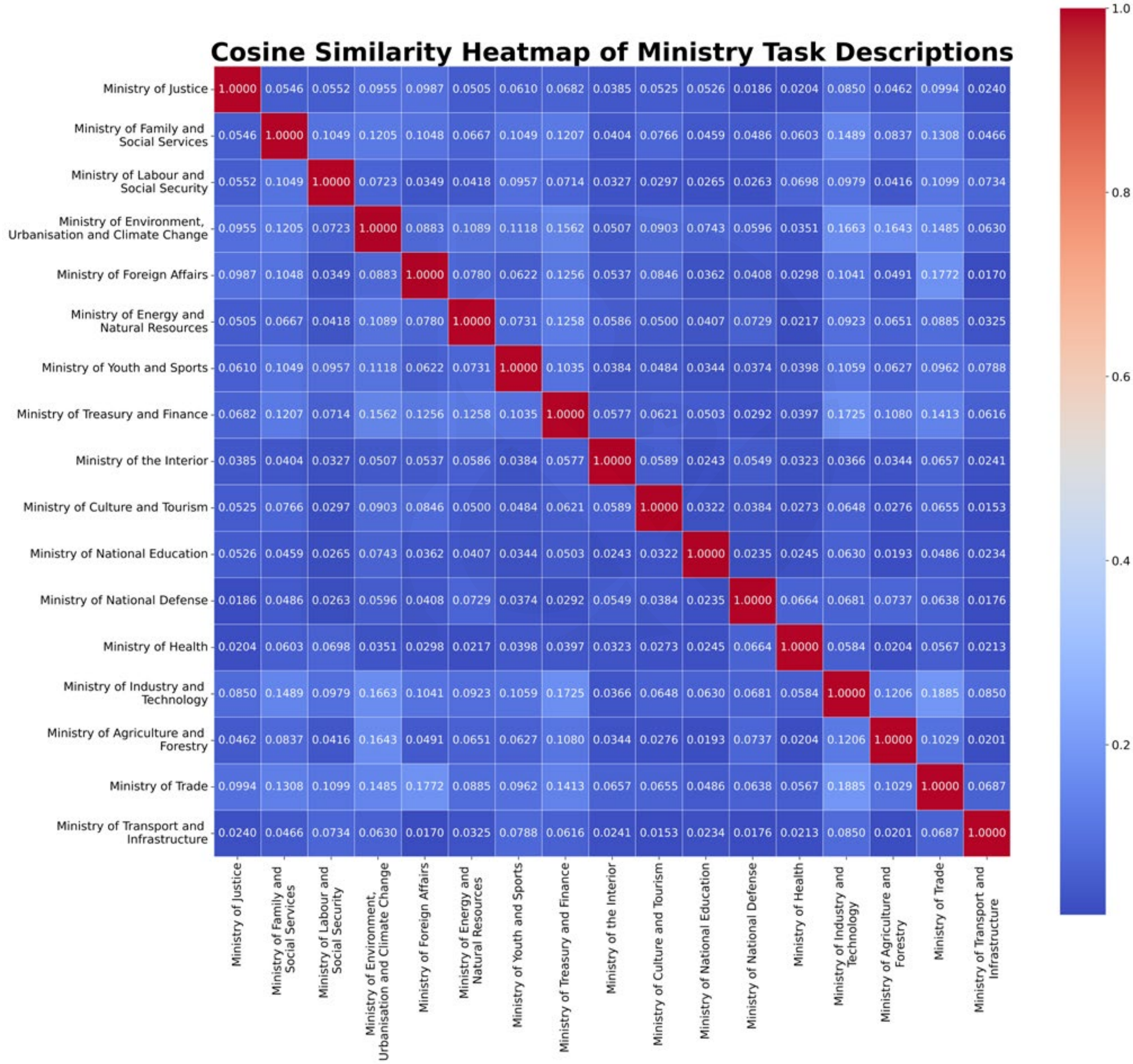


According to this figure, each additional class added to the classification problem increases the complexity of the classification layer and extends the model's convergence time. Therefore, in this study, the data in the dataset used in the training process of AI models was limited to four different categories as applications submitted for the "Republic of Türkiye Ministry of National Education" (MNE), "Republic of Türkiye Ministry of Health" (MH), "Republic of Türkiye Ministry of Transport and Infrastructure" (MTI) and other ministries (OM) to reduce the computational cost, and the automation process was performed for these four categories. All analyses were performed on a system equipped with an AMD Ryzen R9 5900HX processor, an AMD Radeon RX 6700M GPU, and 32 GB of RAM. While this setup is sufficient for medium-scale DL tasks, it imposes practical limitations when training larger models. Therefore, reducing the number of categories was a necessary step to ensure the feasibility of the study.

In this study, the selection of ministries was performed by considering the three ministries whose scopes of responsibility exhibit the least similarity with those of the others, in order to improve the accuracy of the TC process. Cosine similarity values for the scopes of responsibility of each ministry were calculated to determine the similarity between the scopes of responsibility. Cosine similarity is a widely used metric in ML and NLP for measuring the similarity between two text or data vectors (Sasoko et al., 2024). Cosine similarity quantifies the semantic similarity or dissimilarity between data or text sets by calculating the cosine of the angle between two vectors, thereby measuring how similar the directions of the vectors are. In this analysis, the scopes of responsibility for all ministries were determined based on Presidential Decree No. 1

issued by the Presidency of the Republic of Türkiye. To enhance the accuracy of the results, conjunctions and other contextually insignificant words were removed from the texts. The heatmap illustrating the cosine similarity values obtained for the ministries' scopes of responsibility is presented in Figure 5.

Figure 5. Cosine similarity heatmap of the scopes of responsibilities for all ministries in Türkiye



The results of the cosine similarity analysis show that the MNE, Ministry, and MTI generally yield the lowest similarity scores. This indicates that the responsibilities of these three ministries are less similar to those of the other ministries. Consequently, these three ministries were selected as the focus of the classification problem addressed in this study.

After the training process, two different AI models were compared, and the most efficient model was determined.

Modern Governance Approach in Türkiye

The main purpose of the existence of states is to provide essential services such as security, shelter, health and education to their citizens (Şahin, 2018, pp. 99–139). In the classical period, by a simple relationship existed between the structures shaped by societal lifestyles and the state systems embodied within these structures (Gündüz & Artar, 2023, pp. 660–700). However, in the modern state, in addition to these services, the protection of fundamental rights and freedoms has gained importance (Şahin, 2018, pp. 99–139). The main reason for this situation is that the state has the power to govern its citizens. Today, international institutions and other organisations can also make binding decisions apart from states. It is seen that these decisions are generally aimed at protecting the individual and putting the citizen in a strong position vis-à-vis the state. In this context, it can be said that states are moving towards a more transparent, accountable and supremacy of law management approach. The concept of "good governance" encompasses this approach, referring to the participation of the people in management and their contribution to the formation of policies (Şahin, 2018, pp. 99–139; Yağmurlu & Eroğlu, 2020, pp. 139–167).

Today's political, social, economic and technological developments necessitate innovation and transformation in public administration (Acar, 2018, pp. 4836–4848; Gündüz & Artar, 2023, pp. 660–700; Şahin, 2018, pp. 99–139). Since the last years of the Ottoman Empire in Türkiye, administrators have made some reforms, but these reforms have led to the strengthening of an oppressive and centralised structure. There has been no significant change in the management approach after the declaration of the Republic (Şahin, 2018, pp. 99–139). However, since the 2000s, significant steps have been taken, particularly in the adoption of governance principles (Güler, 2020, pp. 273–287; Şahin, 2018, pp. 99–139; Saylam, 2020, pp. 23–37). In this context, Law No. 4982 on the Right to Information, which entered into force in 2004, has brought about a significant change in public administration based on the principles of transparency and democratic management. In addition, the ability to apply for information through digital platforms such as CİMER is an important development in terms of e-participation (Acar, 2018, pp. 4836–4848; Dede, 2024, pp. 355-365; Dede, 2025, pp. 963-990; Durmuşoğlu & Genel, 2022, pp. 70-90; Güler, 2020, pp. 273–287; Şahin, 2018, pp. 99–139;

Saylam, 2020, pp. 23–37; Üz & Kara, 2024, pp. 337-356). In today's world, where the concept of the digital age is frequently on the agenda, when it comes to the right to information and petition, the first e-government application that comes to mind in Türkiye is CİMER (Acar, 2018, pp. 4836–4848). When a citizen thinks that their request for information is not met, they can make their objections and complaints to the administrative courts, the Ombudsman Institution or the Information Acquisition Evaluation Board (Güler, 2020, pp. 273–287; Şahin, 2018, pp. 99–139).

Fundamental Approaches and Methodologies in Text Classification

The fundamental theoretical approaches in the field of TC can be broadly categorised into traditional statistical methods, feature selection and representation techniques, DL-based models, and semantic-oriented approaches.

Early methods used in TC are based on representing texts as vectors of word frequencies and applying statistical or ML algorithms (e.g., Naive Bayes, Support Vector Machines, Decision Trees, and K-Nearest Neighbours) to these vectors. These methods often adopted the "bag of words" model, in which the position, order, and syntactic relationships between words are disregarded. While computationally efficient, such models are limited in their ability to capture semantic meaning and contextual nuance (Li et al., 2022, pp. 1-41; Altınel & Ganiz, 2018, pp. 1129-1153; Strimaitis et al. 2022).

In TC, feature selection techniques such as Information Gain and Maximum Discrimination are applied to handle high-dimensional and noisy data. Additionally, word embeddings such as Word2Vec and GloVe have been utilised to represent words in dense vector spaces based on their semantic similarity. This representation allows the model to understand the contextual relationships between words more effectively than frequency-based representations (Tang et al., 2016, pp. 1602-1606; Altınel & Ganiz, 2018, pp. 1129-1153; Strimaitis et al. 2022).

In recent years, DL has brought significant advancements in the field of TC. CNNs can capture local patterns and n-gram-like structures in text data. Recurrent Neural Networks and their extensions, such as Long Short-Term Memory networks, excel in modeling the sequential nature of language. More recently, transformer-based models, particularly BERT (Bidirectional Encoder Representations from Transformers), have demonstrated state-of-the-art performance by leveraging attention mechanisms to model complex contextual dependencies. These models do not require manual feature engineering and can learn high-level semantic representations directly from raw text (Li et al., 2022, pp. 1-41; Minaee et al., 2021, pp. 1-40).

Semantic-oriented approaches go beyond the traditional bag-of-words paradigm by incorporating contextual meaning and relationships between words. These models exploit semantic similarity, contextual encoding, and embeddings to achieve more accurate classifications. In particular, BERT and similar models dynamically interpret each word in its full sentence context, enabling nuanced understanding and improving classification accuracy in complex textual environments (Altınel & Ganiz, 2018, pp. 1129-1153).

METHODOLOGY

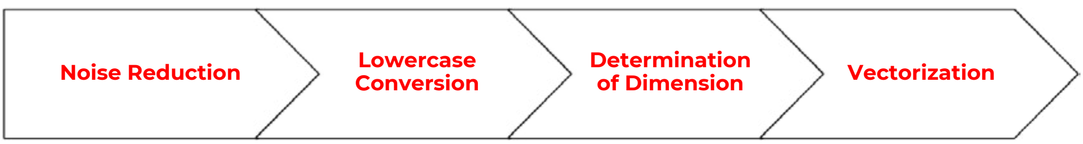
Creating the Dataset Used in AI Models

In this study, the dataset is limited to 6000 samples because the training process of the BERT model requires high system requirements and computational costs. To prevent the imbalance problem in training ML algorithms, four categories were selected: MTI, MNE, MH, and OM. A balanced dataset was created by selecting 1500 data points for each category, and the applications were kept in the range of 150-500 words for the BERT model to work efficiently (Branco et al., 2016, pp. 1-50). The dataset used in this study is not based on actual applications and does not contain any personal data. All texts are artificially generated using the GPT-4 model and are not associated with any real person, institution, or event. In the production of the data, the goal is to create realistic yet completely original and random content. From the literature, it can be seen that the success of the GPT-4 model in creating realistic text data is quite high (Stribling et al., 2024, pp. 1-11).

Pre-processing of Data in the Dataset

Data preprocessing is the first step for TM algorithms and includes removing noisy data in order to increase data quality (Dorukbaşı, 2023; Pilavcılar, 2007; Özkan & Kar, 2022, pp. 504-519). Various preprocessing methods are applied in the literature depending on the purpose of the study. The aim of preprocessing is to reduce the data to a meaningful and normal form before ML techniques (Salur & Aydın, 2019). Therefore, considering the characteristics of the data used in this study, all characters were converted to lower case letters, punctuation marks, numbers, HTML tags and stopwords were deleted in the text (Figure 6). In this process, Python-based NLTK and RegEx libraries were used (Şahin & Diri, 2021; Sel & Hanbay, 2021, pp. 675–684; Yılmaz & Yumuşak, 2021, pp. 81–85).

Figure 6. Preprocessing steps used for TC



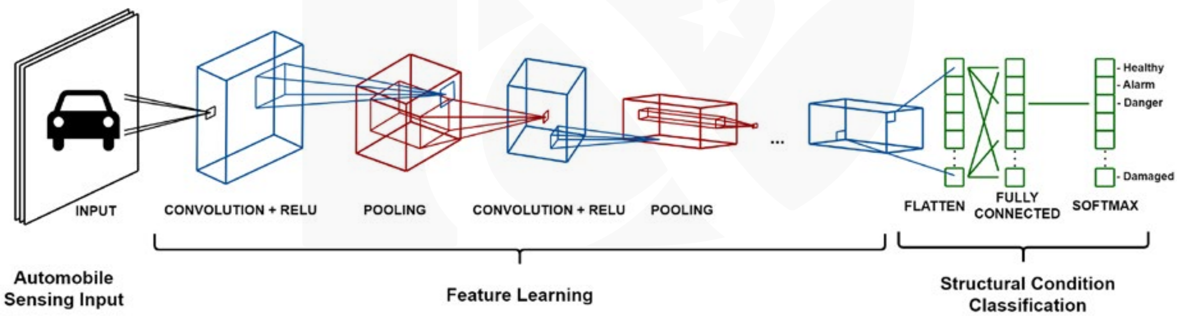
The feature extraction process for the CNN model was performed using the index-based coding method, which is economical in terms of computational cost, easy to implement, and the most widely used in the literature (Bayrak et al., 2021, pp. 3589–3607). The feature extraction process for the BERT model was performed using the BERT embedding method, both because of its capacity to understand the context of the text and then predict embeddings for each word, and because the outputs to be obtained as a result of the feature extraction process can be in a format that can constitute input to the pre-trained BERT network used in this study (Dorukbaşı, 2023; Helli et al., 2023).

Creating AI Models for Classifying Applications

Creating the CNN Model:

CNN, a type of ML, is a type of artificial neural network (ANN) that processes data with a grid topology and uses convolution and pooling layers (Ay Karakuş, 2018; Goodfellow et al., 2016; Salur & Aydın, 2019; Taşağal, 2019; Taşar et al., 2021). A typical CNN structure is shown in Figure 7.

Figure 7. A typical CNN architecture



DL algorithms are more useful for problems with high-dimensional data (Ay Karakuş, 2018; Salur & Aydın, 2019; Şeker et al., 2017, pp. 47–64). Therefore, in this study, the CNN model was used as the DL model. The dimensionality of the CNN model was reduced to 1D due to the one-dimensionality of the texts in the dataset used (Acı & Çırak, 2019, pp. 219–228; Ay Karakuş, 2018). In this study, considering both the computational cost and the literature review, the CNN model consisting of an input layer, an embedding layer, a convolution layer, a pooling layer, a dropout layer, a flatten layer, a fully connected layer and an output layer was used (Alparslan & Dursun, 2023, pp. 21–31; Erkırtay & Ünal, 2021, pp. 168–185).

The data partitioning process was performed automatically, the data was divided into training and validation data according to the standard partition ratio of 0.2, and the number of data in the test data set was selected as 20% of the total data in the data set (Çelikten & Bulut, 2021; Özdemir & Türkoğlu, 2022, pp. 517–529).

In this study, in order to reduce the computational cost, considering the literature review, the values of 8, 16 and 32 were selected as the output size parameter for the CNN model; ReLU activation function was used in the convolution and fully connected layers, and Softmax function was used in the output layer (Acı & Çırak, 2019, pp. 219–228; Alparslan & Dursun, 2023, pp. 21–31; Ay Karakuş, 2018; Özdemir & Türkoğlu, 2022, pp. 517–529). L1 regularizer was used as the regularizer, bias values were initialised using a small and positive constant number, and Adam optimiser was used as the optimisation algorithm (Acı & Çırak, 2019, pp. 219–228; Bock et al., 2018; Goodfellow et al., 2016). The values of 0.001, 0.0001 and 0.00001 were used as the learning rate, and 10-7, 5x10-8 and 10-8 were used as the epsilon value (Ay Karakuş, 2018; Özkan & Kar, 2022, pp. 504–519; Sel & Hanbay, 2021, pp. 675–684).

Considering the literature review, the batch size values were selected as 16, 32 and 64, and the number of epochs as 2, 7, 25 and 100 Şahin & Diri, 2021; Tuncer et al., 2021, pp. 243–252). The optimum hyperparameter values were found by trial and error using the Keras library (Ay Karakuş, 2018; Sel & Hanbay, 2021, pp. 675–684). The optimum parameter values of the CNN model, created for the selected parameter value ranges, are shown in Table 1.

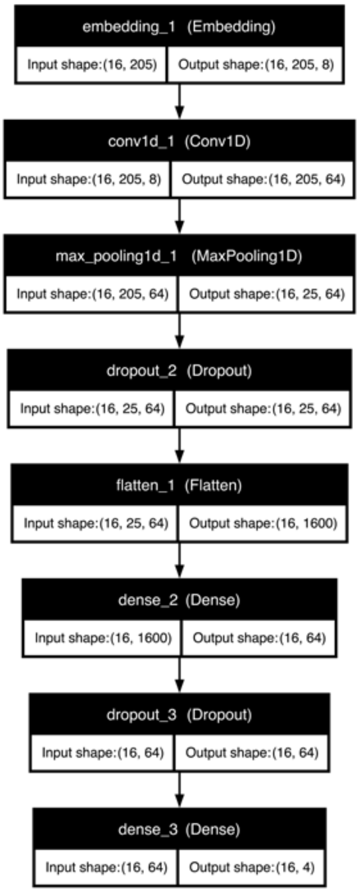
Table 1. Optimum parameter values for the CNN model

Parameter	Optimum Value	Parameter	Optimum Value
Regularizer-1	0.001	Dimension of filter in pooling layer	8
Regularizer-2	0.0015	Output size for embedding layer	8
Bias-1	0	Number of neurons in fully connected layer	64
Bias-2	0	Learning rate	0.001
Dropout-1	0.4	Epsilon	5x10-8
Dropout-2	0	Batch size	16
Number of filters in convolutional layer	64	Number of epochs	100
Dimension of filter in convolutional layer	4		

In Table 1, the term Regularizer-1 represents the regularizer added to the convolution layer, the term Regularizer-2 represents the regularizer added to the fully connected layer, the term Bias-1 represents the bias value added to the convolution layer, the term Bias-2 represents the bias value added to the fully connected layer, the value Dropout-1 represents the dropout rate in the dropout layer after the pooling layer added after the convolution layer, and the value Dropout-2 represents the dropout rate used in the dropout layer added after the fully connected layer.

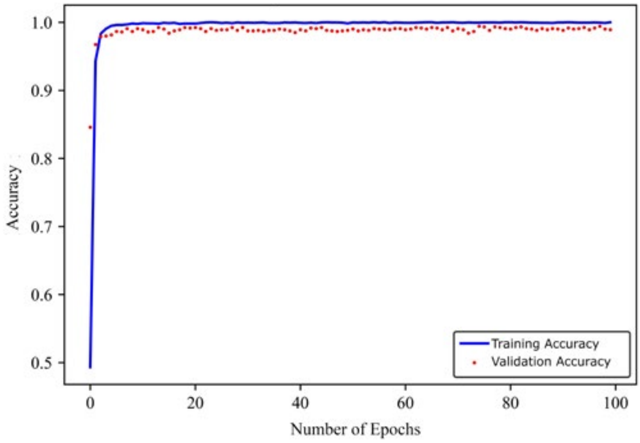
The architecture of the CNN model created by considering the parameters in Table 1 is shown in Figure 8.

Figure 8. Architecture of the CNN model created within the scope of this study



The learning curve of the CNN model used is shown in Figure 9. According to this figure, it is seen that the validation accuracy value of the created model is equal to 99.336% and the test accuracy value is equal to 98.223%. This shows that there is no incomplete learning problem in the created CNN model.

Figure 9. Learning curve for CNN model



Creating the BERT Model:

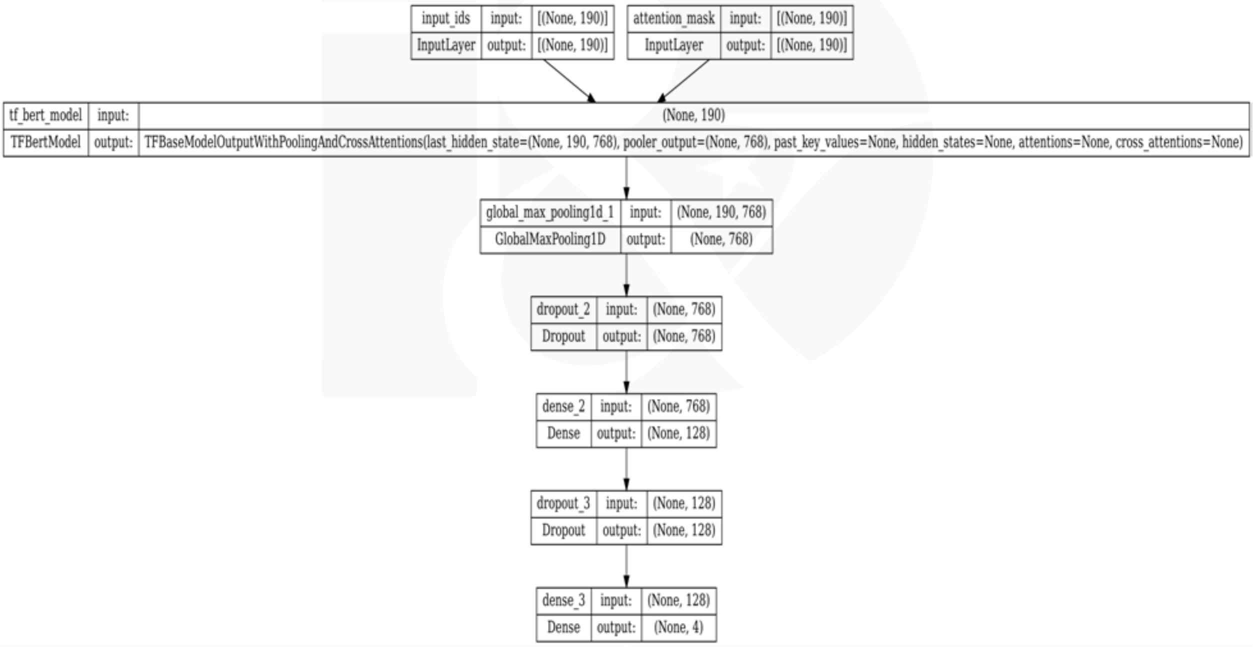
In this study, the "dbmdz/bert-base-turkish-cased" model and tokeniser from the Hugging Face platform are used (Ay Karakuş, 2018; Koçak & Yiğit, 2023, pp. 277–285). BERT-BASE architecture has 12 transformer blocks, 768 hidden layers and 12 self-attention heads (Alparslan & Dursun, 2023, pp. 21–31). In addition, this model contains 128,000 Turkish words (Dorukbaşı, 2023). In this study, considering both the computational cost and the literature review, the BERT model consisting of the input layer, the BERT layer including embedding and network architecture, the pooling layer, the dropout layer, the fully connected layer and the output layer is used (Şeker et al., 2017, pp. 47–64; Taşağal, 2019). In addition, in order to make a more reasonable comparison with the created CNN model, the same pooling method, the same activation functions, the same weight and bias initialisation method, the same regularizer and the same optimisation algorithm were used in the BERT model as the CNN model. Unlike the CNN model, in the BERT model, the bias and regularizer values and the ReLU activation function were added only to the fully connected layer. In addition, the pooling layer was used only after the BERT layer, and the dropout layer was used after the pooling layer and the fully connected layer.

The optimum hyperparameter values for the selected parameter ranges in the BERT model were determined through trial and error using the Keras library, similar to the approach taken for the CNN model. The Dropout-1 value in this table indicates the dropout rate in the dropout layer added after the pooling layer, and the Dropout-2 value indicates the sparsity rate used in the dropout layer added after the fully connected layer. The optimum parameter values of the created BERT model are shown in Table 2.

Table 2. Optimum parameter values for the BERT model			
Parameter	**Optimum Value**	**Parameter**	**Optimum Value**
Regularizer	0.0005	Learning rate	0.0001
Bias	0	Epsilon	5x10-8
Dropout-1	0.4	Batch size	32
Dropout-2	0.7	Number of epochs	25
Number of neurons in fully connected layer	128		

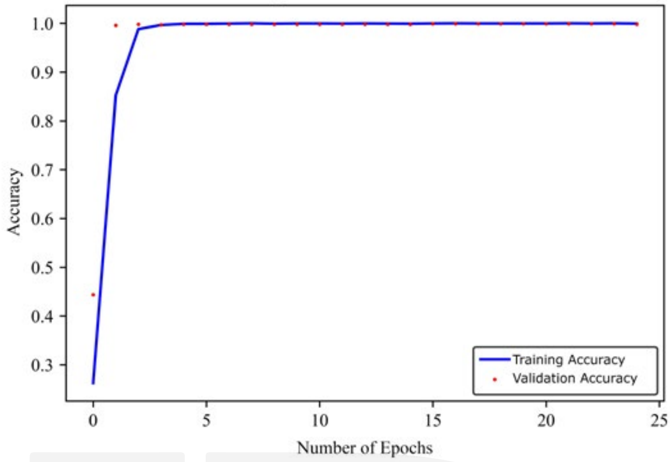
The architecture of the BERT model created by considering the parameters in Table 2 is shown in Figure 10.

Figure 10. Architecture of the BERT model created within the scope of this study



The learning curve of the BERT model used is shown in Figure 11. According to this figure, it is seen that the validation accuracy value of the created model is equal to 99.986% and the test accuracy value is equal to 99.924%.

Figure 11. Learning curve for BERT model



Results and Discussions

The accuracy of predictions made by AI algorithms and the efficiency of these algorithms can be measured by the accuracy, precision, recall, and F1 score values calculated according to the following equations using predicted values and actual values (Acı & Çırak, 2019, pp. 219–228; Alparslan & Dursun, 2023, pp. 21–31; Şahin & Diri, 2021; Şeker et al., 2017, pp. 47–64; Taşağal, 2019; Yılmaz & Yumuşak, 2021, pp. 81–85).

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1 Score} = 2*\frac{\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}} \quad (4)$$

The expressions TP, TN, FP, FN in the above equations represent true positive, true negative, false positive and false negative values, respectively. True Positive refers to instances that are actually positive and correctly predicted as positive. True Negative refers to instances that are actually negative and correctly predicted as negative. False positives correspond to instances that are actually negative but incorrectly predicted as positive. False Negative refers to instances that are actually positive but incorrectly predicted as negative. Precision indicates the proportion of instances predicted as positive that are actually positive. Recall measures the proportion of actual positive instances that the model correctly identifies. The F1 score is the harmonic mean of precision and recall, providing a metric that balances both measures. Considering the literature reviews, the metrics mentioned above were taken into consideration in this study (Alparslan & Dursun, 2023, pp. 21–31; Çelikten & Bulut, 2021; Güven, 2023, pp. 1–6; Helli et al., 2023; Özkan & Kar, 2022, pp. 504–519; Taşağal, 2019; Tuncer et al., 2021, pp. 243–252).

The values of accuracy, precision, recall and F1 score calculated using the values predicted through the created AI models and actual values are shown in Table 3.

According to Table 3, the highest precision was obtained for applications made to the MTI and OM, the highest recall was obtained for applications made to MH and MNE, and the highest F1 score was obtained for applications made to MNE in the CNN model. However, the highest precision was obtained for applications made to the MH, MNE and OM, the highest recall was obtained for applications made to MNE, MTI and OM, and the highest F1 score was obtained for applications made to MNE and OM in the BERT model. In addition, it is also seen that the BERT model has higher precision, recall, F1 score and accuracy values compared to the CNN model.

Table 3. Metrics that are calculated using values predicted by AI models and actual values

Architecture of the model used	Metric	Republic of Türkiye Ministry of Health (MH)	Republic of Türkiye Ministry of National Education (MNE)	Republic of Türkiye Ministry of Transport and Infrastructure (MTI)	Other Ministries (OM)
CNN	Precision	0.941	0,996	1.000	1.000
	Recall	0.996	0.996	0.946	0.987
	F1 score	0.968	0.996	0.972	0.994
	Accuracy	0.982			
BERT	Precision	1.000	1.000	0.997	1.000
	Recall	0.997	1.000	1.000	1.000
	F1 score	0.998	1.000	0.998	1.000
	Accuracy	0.999			

In addition, in the case of selecting the optimum parameters, it was seen that the BERT model has approximately 273 times more parameters than the CNN model. Therefore, it can be concluded that the CNN model created is more advantageous than the BERT model in terms of computational cost. However, even an extremely minimal rise in the percentage of correctly classified applications will result in significant savings of public resources and the human resources used in the referral process of the CİMER applications, considering the great number of applications submitted to the CİMER system. Therefore, the BERT model is more advantageous than the CNN model from a general perspective.

Upon reviewing the existing literature, it is observed that no studies have focused on automating the CİMER system or classifying applications submitted to CİMER. However, although limited in number, some studies on TC within the public sector exist (Aydın, 2020; Binici, 2019, pp. 116-126; Çelik, 2023; Göker & Tekdere, 2017, pp. 291-299; Şahin et al., 2024, pp. 116-126; Yılmaz & Dikbaş, 2013, pp. 79-86). Therefore, this study has been compared with the studies mentioned above (Table 4). The following criteria were taken into consideration: the analytical method used, the number and type of data in the dataset, the purpose of the study, and the accuracy achieved as a result of conducting this comparison. Since none of the reviewed studies included an analysis of computational cost, this aspect was excluded from the comparison.

Compared to existing studies on text classification in the public sector, the BERT-based approach proposed for automating the referral process of CİMER applications demonstrates significant superiority in terms of both classification accuracy and practical applicability. Göker and Tekedere (2017) classified opinions regarding the FATİH project using the Sequential Minimal Optimisation algorithm. They achieved an accuracy of 88.73%. Yılmaz and Dikbaş (2013) employed a decision tree method on public construction dispute documents but did not report any accuracy value. In the study conducted by Çelik (2023), a qualitative analysis was performed using computer-assisted qualitative data analysis software (CAQDAS) tools, such as NVivo. While methodologically rich, the study lacks algorithmic scalability and quantifiable performance outcomes. Şahin et al. (2024) carried out a lexicon-based sentiment analysis on 1,584 patient comments, yet they did not provide any accurate results. Aydın (2020) used several classifiers, including multilayer perceptron and gradient boosting, achieving up to 90.91% accuracy. Binici (2019) applied the support vector machine algorithm to official documents and reported an accuracy of 87.72%. Despite the methodological variety of these studies, none approaches the exceptional classification accuracy (99.92%) or the multi-ministry operational compatibility demonstrated by the proposed BERT-based model in this study. The proposed approach offers an optimized, scalable (with appropriate fine-tuning), and automation-ready solution, making it the most accurate among current studies and the most practically implementable.

Table 4. Comparison of this study with existing studies in the literature

Accuracy	The aim of the study	Dataset	Method	Criterion
Maximum 90.91%	Classification of judicial rulings concerning workplace mobbing	A total of 131 rulings issued by the Turkish Court of Cassation	Logistic regression, decision tree, k-nearest neighbours, gradient boosting classifier, AdaBoost classifier, bagging classifier, random forest classifier, multilayer perceptron classifier	Aydın (2020)
87.72%	Document classification	A total of 112 documents referred by the departments of Çankırı Karatekin University	Support vector machine	Binici (2019)
The study does not report any accuracy value	Detection of problems in public procurement practices in Turkey using text mining techniques	A total of 406 decisions by the Public Procurement Authority	Computer-assisted qualitative data analysis software	Çelik (2023)
88.43%	Opinion classification concerning the FATİH project	A total of 444 user opinions concerning the FATİH project	Sequential minimal optimisation algorithm	Göker & Tekdere (2017)
The study does not report any accuracy value	An analysis of patient satisfaction at Antalya Training and Research Hospital	A total of 1584 patient reviews	Lexicon-based method	Şahin et al. (2024)
88.23%	Classification of dispute documents in the Turkish public construction sector	A total of 49 decision documents from the Supreme Board of Infrastructure	Decision tree	Yılmaz & Dikbaş (2013)
99.92%	Automation of the referral process for CİMER applications	A total of 6000 CİMER applications	BERT	This study

Conclusions

In the modern state understanding, the protection of fundamental rights and freedoms has an important place. In this context, various innovations have been introduced in public administration in Türkiye, and the CİMER system has emerged as an important development in this regard. However, this situation brings with it an increase in the number of applications, human resources and efficiency problems. Therefore, it is of great importance to automate the referral process of applications made to the CİMER system to the maximum extent.

In this study, an innovative novel approach has been proposed for automating CİMER applications using AI methods. This approach involves classifying citizens' applications using an AI model to forward them to the correct institution and automatically refer the application. The performance of the AI models created using the CNN and BERT methods has been evaluated on applications submitted to the CİMER system, and the most efficient model has been determined. As a result, applications forwarded to the CİMER pool system for MTI, MNE, and MH have been automatically referred without the need for manual intervention. As a result of this study, it was observed that the proposed approach is highly efficient in terms of providing savings in the public sector and promoting the more efficient use of human resources.

The optimal hyperparameter values and the most suitable AI model vary depending on the nature of the problem and the structure of the dataset used. In this study, since the classification was performed for only three ministries, the developed AI model cannot be directly generalised to all ministries. However, as illustrated in the heatmap in Figure 4, most of the cosine similarity values for the scopes of responsibility of the ministries are below 0.1 (10%). This indicates that there are significant differences among the data in the dataset (which includes the scopes of responsibilities of the ministries) subjected to similarity analysis. Therefore, the BERT model developed in this study can potentially be applied to other ministries, provided that appropriate fine-tuning is performed. If the model can be adapted for all ministries, the proposed AI-based approach could be integrated into the CİMER system, as illustrated in Figure 3, enabling an automated referral process for applications submitted to all ministries. Nevertheless, it is not easy to reach a definitive conclusion at this stage, as the choice of the optimal AI model depends heavily on the characteristics of the dataset. Therefore, to more accurately evaluate the generalisability of the proposed model, the BERT model created in this study should be fine-tuned for a dataset that includes all ministries, and the assessment should be conducted following this refinement.

Although the performance of the suggested method has been evaluated using synthetic data in this study, it is recommended that testing this method with actual data would provide a better understanding of its effectiveness. Testing the proposed method with actual CİMER data may reveal other aspects of its potential and verify its effectiveness in reality.

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