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A Data Driven Forecasting Model for Active Offenders on Electronic Monitoring Systems in Türkiye

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ABSTRACT

The electronic monitoring of offenders is an increasingly popular technique in the criminal justice system. Worldwide, these systems are effectively utilized to monitor individuals on probation as they serve their sentence within the community. The use and significance of electronic monitoring systems are increasing day by day in Türkiye. This paper presents a CEEMDAN and Kernel based Meta-Extreme Learning Machine hybrid forecasting model using data on active offenders convicted of different crimes between 2013 and 2021 in Türkiye. Thanks to the proposed model, it is aimed to plan the equipment that will be needed and to provide optimal system management by observing the development of electronic monitoring systems in Türkiye. To validate the proposed model, it is compared with some state of the art model. The superiorty of the proposed model is shown using some performance metrics. Moreover, the current status of electronic monitoring systems in Türkiye from past to present is shown statistically. While most studies on electronic monitoring focus on its financial or legal dimension, this paper performed a data driven forecasting approach for optimal planning.

1. Introduction

Probation offers individuals the opportunity to fulfill their sentence within the community, under close surveillance and supervision, as an alternative to arrest or imprisonment following a court conviction [1]. With the advancements in technology, electronic monitoring has emerged as a viable alternative to incarceration, serving as a condition of probation or as an integral component of parole decisions.

In the early 1990s, electronic monitoring emerged as a significant aspect of European criminal policy. The United Kingdom, Wales, Sweden, and the Netherlands were pioneers in adopting electronic monitoring as a primary punitive measure, offering it as an alternative to incarceration following conviction, early release from prison, or even prior to sentencing [2]. In the early 2000s, several countries embraced electronic monitoring, including Portugal, Italy, France, Belgium, and Scotland. Presently, legislation on electronic monitoring has been enacted in Austria, Denmark, and various Eastern European nations. Switzerland and Spain continue to conduct localized experiments with electronic monitoring. Meanwhile, in Germany, the state of Hessen initiated a pilot program for electronic monitoring in 2000, which eventually expanded to encompass all states within the country [3].

The existing literature on electronic monitoring systems encompasses numerous studies examining diverse perspectives, ranging from social-cultural analyses to engineering-oriented investigations [4, 5, 6]. Güler et al. [7] performed comparative analyses of probation practices and electronic monitoring systems across various countries. Examination of developed methods revealed that each country employs distinct types of electronic monitoring approaches tailored to their specific needs, with these diverse needs being interpreted accordingly. According to Hucklesby et al. [8] 72.2% of the prisoners stated that electronic monitoring helped change their lifestyle, 61.2% found it effective in keeping them away from their criminal friends, and 74.1% mentioned that they spent more time with their families, leading to improved and stronger relationships.In their report, Padgett et al. [9] highlighted that cohabiting with convicts in the community significantly diminishes threats to public safety. Electronic monitoring serves as a deterrent against escape attempts and lowers the likelihood of committing new crimes. In addition, several studies have reported that longer periods of incarceration increase the likelihood of recidivism, whereas longer periods of electronic surveillance reduce it [10].

Despite the development of artificial intelligence techniques, their application in crime prediction remains limited. Furthermore, while data-driven models analyzing the changing number of individuals under electronic monitoring exist, they do not prioritize future system planning. Although prediction and classification analyses based on past crime data are conducted using popular artificial intelligence (AI) techniques [11, 12, 13, 14, 15, 16], there is a lack of specific models and studies pertaining to electronic monitoring systems.

The main purpose of this study is to develop a forecasting model on electronic monitoring systems. The proposed model is based on incorporating CEEMDAN and Kernel functions into a Meta-Extreme Learning Machine (Meta-ELM) forecasting method. A short-term forecast was conducted to estimate the number of active offenders in electronic monitoring systems, based on data from 56,857 individuals who were monitored between 2013 and 2021 under the Republic of Türkiye Ministry of Justice. The CEEMDAN technique is employed to reduce data non-linearity and non-stationarity, while Kernel functions improve the stability of

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the Meta-ELM algorithm. To test and validate the proposed hybrid model, its performance is compared with that of deep-learning and traditional forecasting models, namely, LSTM, standalone ELM, MLP, and Meta-ELM.

The remainder of this paper is organized as follows. The CEEMDAN and Kernel based Meta-ELM are introduced in Section 2. Section 3 presents data description, forecasting results and analysis. The final section of this paper comprises the conclusions drawn from the findings and analysis.

2. Material and Methods

2.1. Complete Ensemble Empirical Mode Decomposition

The Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is a powerful signal processing technique used to extract intrinsic mode functions (IMFs) from non-linear and non-stationary data. It addresses the limitations of traditional Empirical Mode Decomposition (EMD) by introducing an adaptive noise term to enhance the decomposition process

Before delving into CEEMDAN, it is important to understand the foundation on which it is built, which is the Empirical Mode Decomposition (EMD). EMD is a data-driven technique that decomposes a given signal into a finite set of IMFs, representing oscillatory modes with varying frequencies and amplitudes. While EMD is effective for many applications, it suffers from mode mixing and end-effect issues. Mode mixing occurs when IMFs with different timescales overlap, making it challenging to separate them accurately. End effects refer to the distortion of IMFs near the boundaries of the analyzed data. CEEMDAN overcomes these limitations by introducing ensemble-based techniques and adaptive noise.

The CEEMDAN algorithm consists of the following steps:

Step 1: At time t, the original signal undergoes the addition of white noise with ω^i, which can be expressed as follows:

$$x^i(t) = x(t) + \varepsilon_0 \omega^i(t), \quad i = 1, 2, ..., N, \tag{1}$$

Here, ε_0 represents the noise coefficient, and N signifies the total number of realizations.

Step 2 The first IMF, denoted as IMF_1, is derived by averaging the constituents of the EMD process [17], expressed as:

$$\overline{IMF_1}(t) = \frac{1}{N} \sum_{i=1}^{N} IMF_1^i(t), \tag{2}$$

Subsequently, the residual process is defined as:

$$r_1(t) = x(t) - \overline{IMF_1}(t). \tag{3}$$

Step 3: Additional decomposition of $r_1(t)+\varepsilon_1 EMD_1(\omega^i(t))$ can be accomplished by applying EMD to calculate the second IMF, while the remaining signal can be represented as:

$$\overline{IMF_2}(t) = \frac{1}{N} \sum_{i=1}^{N} EMD_1(r_1(t) + \varepsilon_1 EMD_1(\omega^i(t))), \tag{4}$$

$$r_2(t) = r_1(t) - \overline{IMF_2}(t). \tag{5}$$

Step 4:The calculation of the m^{th} residual and $(m+1)^{st}$ IMF component is determined based on the procedures outlined in steps 2 and 3 as follows:

$$r_m(t) = r_{m+1}(t) - \overline{IMF_m}(t), m = 2, ..., M, \tag{6}$$

$$\overline{IMF}_{m+1}(t) = \frac{1}{N} \sum_{i=1}^{N} EMD_1(r_m(t) + \varepsilon_m EMD_m(\omega^i(t))), \tag{7}$$

Here, $\overline{IMF}_{m+1}$ corresponds to the $(m+1)$th IMF mode derived through the CEEMDAN algorithm, while $EMD_m(.)$ represents the calculation of the m-th IMF mode using the EMD technique

Step 5:Step 4 is iterated until the IMF component and residual reach a negligible threshold where further decomposition by EMD is not possible. Ultimately, the decomposed signal X(t) can be computed as follows:

$$X(t) = \sum_{m=1}^{M} \overline{IMF}_m(t) + R(t), \tag{8}$$

Here, the final residue $R(t)$ captures temporal trends within the time series

2.2. Kernel based Meta-Extreme Learning Machine

The Extreme Learning Machine (ELM) architecture exhibits a topological structure that closely resembles other well-known neural networks, including the Back Propagation Neural Network and the radial basis neural network. Among various neural network architectures, the ELM has emerged as a powerful and efficient approach. ELM is known for its unique characteristics, including fast learning speed, easy implementation, and good generalization performance. This section provides an overview of the ELM architecture, its key components, and its applications in different domains.

The fundamental structure of the ELM consists of a single-layer feed-forward neural network (SLFN) which comprises three layers: the input layer, the hidden layer, and the output layer. Unlike traditional neural networks, where the weights connecting the input and hidden layers are iteratively adjusted through backpropagation, ELM adopts a different strategy. In ELM, the weights connecting the input and hidden layers are randomly assigned and fixed, making the learning process extremely fast.The output of the single-layer feed-forward neural network (SLFN) is determined based on the input and connections as follows:

$$f(x) = \sum_{j=1}^{N_h} \theta_j \varphi(x\omega_j + b_j). \tag{9}$$

Here, the input connection weights are denoted as ω_j, biases as b_j , and connection weights as θ_j. The number of hidden layers, N_h, as well as the bias and input link weights, are determined randomly. The analytical calculation of θ_k is performed by following the steps outlined below. In this paper, input data $x \in \mathbb{R}^n$ is created by the sliding window technique in this paper. n is the numbers of inputs. In this paper, one-step ahead forecasting is investigated with three previous data and instant data set.

Given that equation (9) encompasses N training samples, it is possible to generate by N equations. These equations can be conveniently expressed using matrix-vector notation, represented as matrix H.

$$H = \begin{bmatrix} \varphi(x_1\omega_1 + b_1) & \cdots & \varphi(x_1\omega_{N_h} + b_{N_h}) \\ \vdots & \vdots & \vdots \\ \varphi(x_N\omega_1 + b_1) & \cdots & \varphi(x_N\omega_{N_h} + b_{N_h}) \end{bmatrix}_{NxN_h} \tag{10}$$

The output weights and the corresponding target values for each output are denoted through the following equation.

$$T = H\gamma, \quad \gamma = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_{N_h} \end{bmatrix}, \quad T = \begin{bmatrix} t_1 \\ \vdots \\ t_N. \end{bmatrix} \tag{11}$$

The computation of the output connection weights involves the calculation of the inverse of the Moore-Penrose matrix H.

$$\hat{\gamma} = H^{+}T. \tag{12}$$

The Meta-ELM network employs multiple ELMs, where each ELM is trained using a specific subset of the dataset. Figure 1 illustrates the architecture of the Meta-ELM network, highlighting the presence of individual ELMs. The output connection weights of the aggregated ELMs are determined through the ELM learning rule, utilizing the complete dataset.

By incorporating kernel functions into the ELM, improved stability and generalization can be achieved. This enhanced version of ELM, referred to as Kernel Extreme Learning Machine or Meta-ELM, is capable of capturing novelty. Thus, the Kernel theorem is formulated as follows

$$K_{ELM} = HH^T, and\ K_{ELM}\left(x_i, x_j\right) = h(x_i)h(x_j) \tag{13}$$

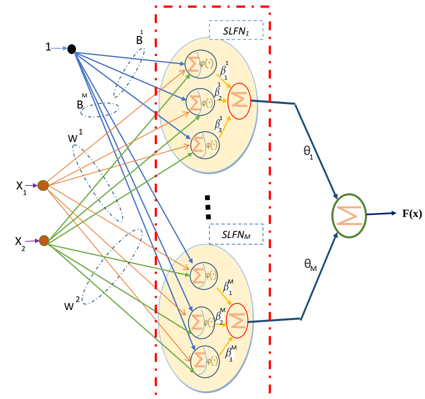

Figure 1: The Meta-ELM architecture

$$f(x) = h(x)H^t(K_{ELM} + \frac{1}{C})^{-1}T \tag{14}$$

where C is the regularization parameter. By considering previous studies [18, 19], the value of C is considered to be 50 in this paper.

Kernel functions fulfill the Mercer condition, rendering them convenient for practical usage. Several Kernel functions can be taken into account, including the Polynomial kernel, Gaussian kernel, Hyperbolic tangent kernel (Sigmoid kernel), and Wavelet kernel. The radial basis function (RBF) kernel is used to analysed in this paper. In the case of the Kernel based Meta Extreme Learning Machine utilizing the kernel function $K(x_i, x_j)$, the equation can be expressed as follows:

$$\left\|K_{NxL}\beta - T\right\|^2 < \varepsilon \tag{15}$$

Here, ε represents a non-zero training error, L is the number of hidden layer samples and N is consistently greater than L. To minimize the error, norm minimization and sample number constraint are employed, resulting in the formulation of the optimization problem as follows:

$$Minimize\ \frac{1}{2}\left\|\beta\right\|^2 + \frac{1}{2}C\left\|\left(K_{NxL}\beta - T\right)\right\|^2 \tag{16}$$

Hence, the output vector can be expressed as follows:

$$\beta = \left[\frac{1}{C} + K_{NxL}^T\ K_{NxL}\right]^{-1} K_{NxL}T \tag{17}$$

Thefore the forecasted output is obtained as

$$f(x) = \begin{bmatrix} K(x, x_1) \\ K(x, x_2) \\ \vdots \\ K(x, x_L) \end{bmatrix} \left[\frac{1}{C} + K_{NxL}^T\ K_{NxL}\right]^{-1} K_{NxL}T \tag{18}$$

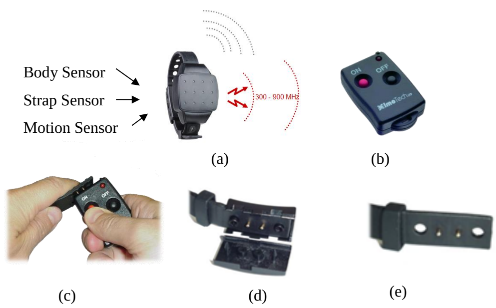

Figure 2: Electronic bracelet and apparatus (a) Clamp, (b) Electronic key, (c) Activation, deactivation and reset, (d) Clip, (e) Strap

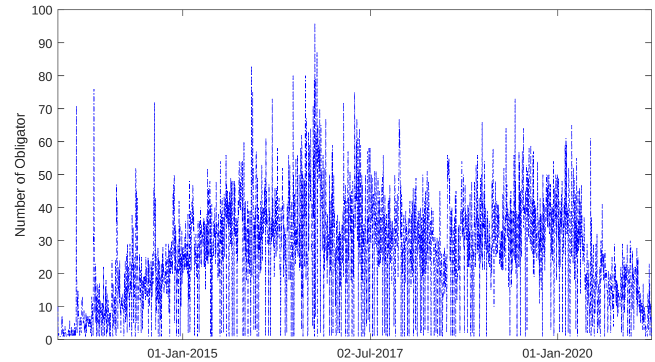

Figure 3: Change in the number of obligator in Türkiye between the years 2013-2021

3. Experimental Results and Discussions

3.1. Description of Electronic Monitoring Data Set

On February 25, 2012, the first pilot application involving 81 offenders from different cities in Türkiye was initiated at the Ministry of Justice General Directorate of Prisons and Detention Houses. This program aimed to test electronic monitoring units, including RF home curfew, GPS tracking, domestic violence, and alcohol monitoring.

Electronic bracelet systems are utilized for a range of purposes, including RF home curfew, GPS tracking, and monitoring cases related to domestic violence. There are RF transmitters integrated into electronic bracelet systems. These transmitters function as sensors, transmitting data to the receiver unit through radio waves. The bracelet itself incorporates three detection sensors: body, strap, and motion sensors (Fig. 2). The body sensor becomes active when the bracelet is removed from the body, while the strap sensor detects any attempts at cutting it. Additionally, the motion sensor helps conserve energy and prolongs the battery life by preventing unnecessary usage. Each bracelet is assigned a unique number and operates within the frequency range of 300-900 MHz. It transmits information to the connected receiver unit via radio waves every 20 seconds. This transmitted data includes crucial information such as the proper attachment of the bracelet to the individual's body, calibration status, battery level, and activation status of the clamp. To enhance security, the bracelet is equipped with special anti-sabotage screws. Once activated, the bracelet can function without requiring energy for three years, and its overall lifespan is limited to five years. However, before the battery is completely depleted after three years, the bracelet transmits the energy level status to the receiver unit through radio waves. Subsequently, the receiving unit utilizes GPRS technology to notify the system operator 7 to 10 days in advance.

Between 2013 and 2021, a total of 56,611 active obligator were monitored, comprising 3,736 women and 52,875 men. Throughout this period, the monitoring system utilized 51,729 home curfew units, 141 alcohol monitoring units, 3,501 GPS tracking units, and 1,240 domestic violence units. Figure 3 shows the change in the number of active obligator over the years.

Monitoring, evaluating and modeling historical data are crucial for system planning and management, particularly in terms of tracking the daily fluctuations in the number of active obligated parties. Therefore, this study focuses on creating a prediction model using data from the period 2013-2021. The original time series data is complete, without any missing values. To preserve the data's inherent characteristics, no noise reduction or smoothing processes were applied. The analysis primarily relies on univariate approaches using historical data alone. In other words, a fixed number of past values serves as the configurable inputs for AI methods. The model's outputs consist of forecasts for future data points in the time series. This learning phase employs a sliding window technique, utilizing a moving time window. Determining the optimal network structure involves considering the width of the input dataset as a significant factor. Consequently, the examination includes measures of association between current and past series values. For the predictive model outputs discussed in the next section, 70% of the original data was used for training and 30% for testing. The flowchart of this study is presented in Fig. 4.

3.2. Analysis of Decomposition Results

The CEEMDAN approach is employed to reduce the non-linear characteristics of the original signal and to improve the performance of the model. Fig. 5 shows a total of nine Intrinsic Mode Functions (IMFs) covering a range from high to low frequencies. IMF_1, denoting the highest frequency component, contains detailed information about the original series. The decomposed signal ultimately reveals the trend in data variation. Artificial intelligence models were utilized to predict all the decomposed IMF signals.

The main challenge of the decomposition-based forecasting step is the prediction of $IMF_1$and IMF_2, due to their high frequency. Figure 6 illustrates the forecasting outcomes for IMF_2. While prediction accuracy is significantly influenced by the highest frequency component, The kernel-based Meta-ELM model performs close to the real data as seen in Fig.6. This method demonstrates a strong correlation.

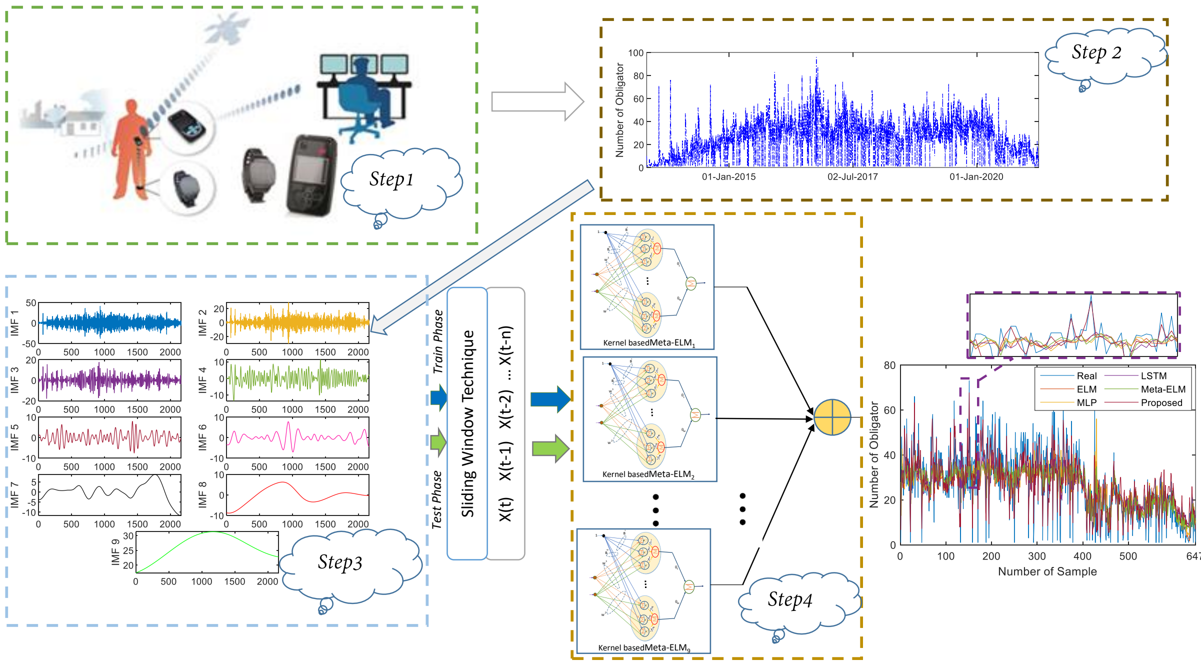

Figure 4: Flowchart of the hybrid forecasting model.

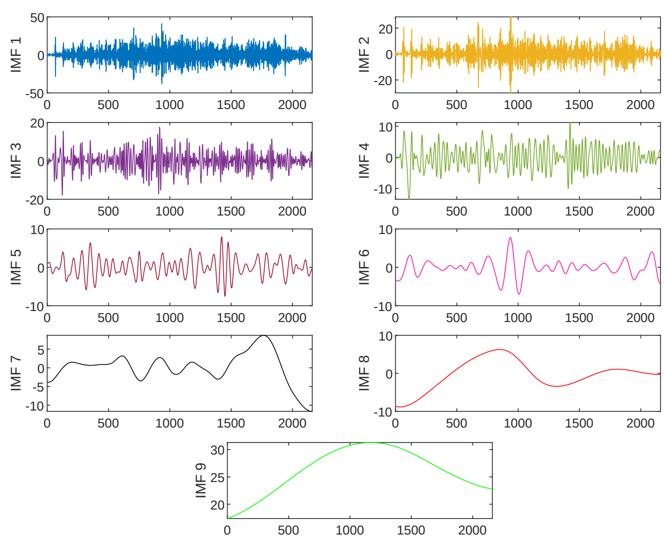

Figure 5: Decomposition of the data based on the CEEMDAN approach

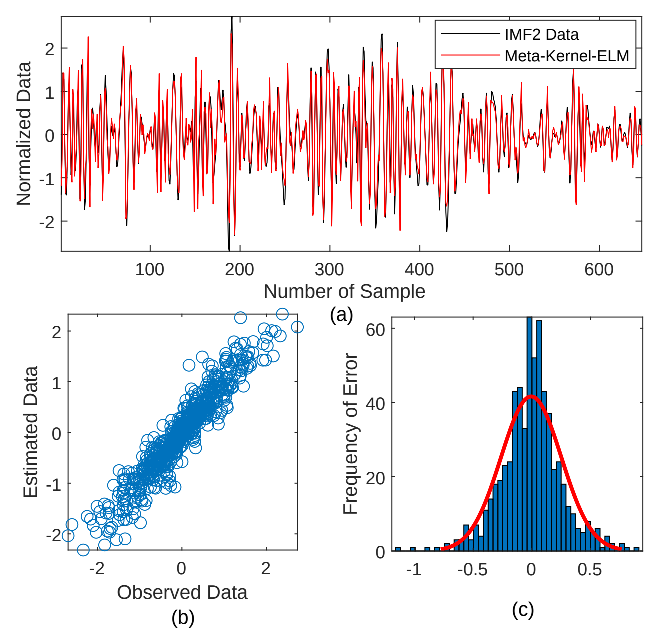

Figure 6: Forecasting results of the IMF 2 Data based on Meta-Kernel-ELM (a) test results (b) regression plot (c) error histogram

To enhance the estimation performance of these components, it is possible to include a multiple decomposition or filtering procedure in the estimation process. Nevertheless, given the excellent performance of the proposed method, no additional filtering or multiple decomposition was utilized in this study. Moreover, it is evident that multiple decomposition would introduce additional time costs to the algorithm.

4. Forecasting Results and Performance Evaluation

In this section, the forecasting results of all implemented models, namely ELM, MLP, LSTM, Meta-ELM and CEEMDAN-Meta-Kernel-ELM are discussed in detail.

Although previous research has employed various forecasting techniques, there is no prevailing model for time series forecasting. While previous research has employed various forecasting techniques, there is no prevailing model for time series forecasting [20]. In this study, we present the performance of a novel hybrid model called CEEMDAN-Meta-Kernel-ELM. Additionally, this research marks the first attempt at conducting forecasting research for planning in electronic monitoring systems. In order to evaluate the effectiveness of the proposed model, a comprehensive comparison is conducted with deep learning and classical forecasting methods.

The performance of all models is assessed by measuring the disparity between the predicted values and the target values in the test dataset. To evaluate the performance of the models, this paper employs RMSE, MSE, and MAE metrics. These metrics, illustrated in Eq (19-21), provide a means to verify the effectiveness of the models.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - y_i')^2}{N}} \tag{19}$$

$$MSE = \frac{\sum_{i=1}^{N}(y_i - y_i')^2}{N} \tag{20}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - y_i'| \tag{21}$$

Here, y_i and y_i' correspond to the actual and predicted values, respectively. N denotes the total number of data points utilized for evaluating and comparing performance. The MAE represents the average absolute error between the forecasted and actual values. The rationale behind utilizing RMSE,MAE is to encapsulate the overall error in forecasting across the entire test dataset.

In order to assess the impact of the proposed decomposition and Kernel based hybrid technique on the forecasting performance, various AI based models have been compared. The models implemented are traditional model; MLP, ELM, improved model; Meta-ELM, deep learning model LSTM, and CEEMDAN-Meta-Kernel ELM (proposed) model. The forecasting test results of the implemented models for the data are shown in Figure 7. The analysis reveals that the proposed model results (highlighted in red) exhibit the closest alignment with the actual data, whereas the LSTM model results demonstrate the highest level of disparities.In order to facilitate a comprehensive comparison of the models' performance, error metrics can be employed. Table 1 presents the values of these error metrics for all the implemented models. In terms of performance metrics, the proposed model outperforms all others, with RMSE, MSE, and MAE values of 7.1955, 51.7759, and 5.7906, respectively. When considering accuracy, the models can be ranked in descending order as follows: proposed (CEEMDAN-Meta-Kernel-ELM), Meta-ELM, ELM, MLP, and LSTM. Their corresponding RMSE values are 7.1955, 11.6030, 11.8025, 11.8422, and 11.9457, respectively.

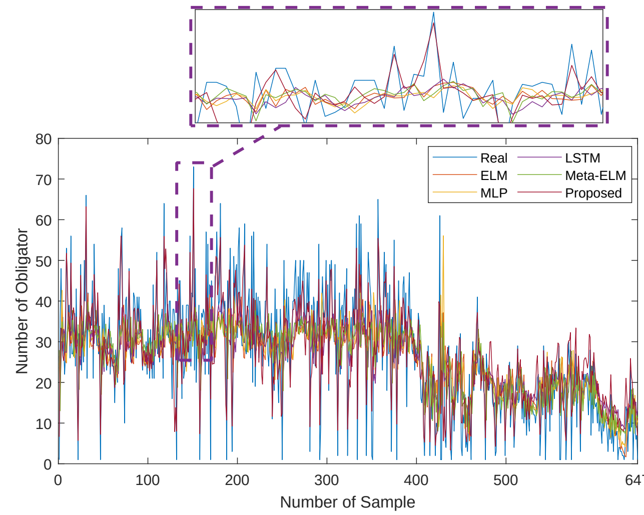

Figure 7: Forecasting test results of the implemented models.

Table 1
Comparative Analysis of Forecasting Results Based on Performance Metrics

Models	RMSE	MSE	MAE
ELM	11.8025	139.2992	8.7960
MLP	11.8422	140.2369	8.8192
LSTM	11.9457	142.6997	9.0301
Meta-ELM	11.6030	134.6287	8.7501
Proposed	**7.1955**	**51.7759**	**5.7906**

To visually illustrate the distinctions among the implemented models, Taylor diagrams are utilized, as depicted in Figure 8. These diagrams effectively demonstrate the interrelationship between the correlation coefficient, root mean square deviation (RMSD), and standard deviation. Consequently, the models can be compared based on their predictive capabilities for the target data. In particular, the proposed method is represented by a triangular red symbol. It is evident from the diagrams that the proposed method exhibits lower RMSD and standard deviation values. Moreover, the correlation coefficient is close to 1. Collectively, these analyses confirm the reliability and effectiveness of the proposed model for forecasting electronic monitoring data.

The simulated results demonstrate that the combination of decomposition and the Kernel-based Meta-ELM algorithm enhances both learning and prediction capabilities compared to single decomposition methods. While ELM, LSTM, Meta-ELM, and MLP models exhibit competitive forecasting performance, the CEEMDAN-Meta-Kernel-ELM model stands out due to its accuarcy. The comprehensive performance analyses unequivocally establish the substantial accuracy improvement achieved by the proposed decomposition and Kernel-based algorithm. In view of these findings, it is anticipated that the proposed estimation methodology will enable the Ministry of Justice to conduct

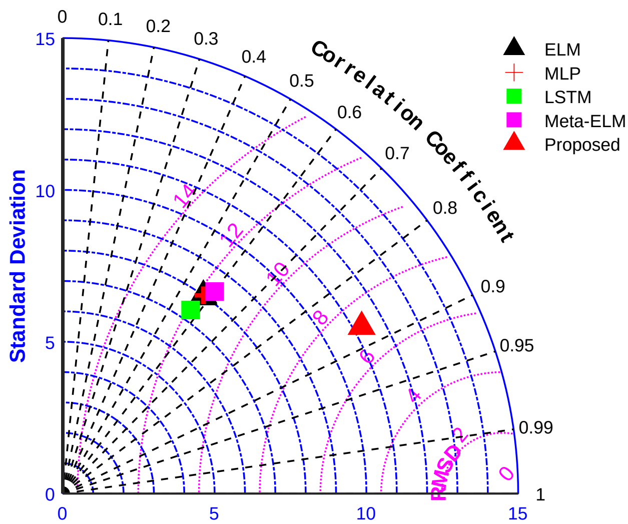

Figure 8: The Taylor diagram of the forecasting models.

planning and management of electronic monitoring systems with enhanced sensitivity and precision.

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5. Conclusions

This paper investigates the application of a novel hybrid forecasting model, namely CEEMDAN-Meta-Kernel-ELM, for electronic monitoring systems. The proposed methodology integrates a signal processing module, CEEMDAN, into the forecasting model to enhance its performance. By applying the CEEMDAN for signal decomposition, the nonlinearity and non-stationarity inherent in the original data are effectively mitigated. Moreover, the inclusion of the RBF Kernel function in the Meta-ELM forecasting model contributes to its stability and further improvement. This study employed daily monitoring data of the number of active offenders in Türkiye from 2013 to 2021 to investigate the research objectives. To validate the proposed model, a comprehensive comparison was conducted against various approaches including deep learning (LSTM), classical models (MLP, ELM), and a recently improved model (Meta-ELM).

The proposed method reduced performance error metrics (e.g., RMSE) by 37.98%-39.76% as compared to the implented models, Meta-ELM and LSTM, respectively. The comparative analysis has demonstrated consistency among the results across other performance metrics. Upon evaluation of the correlation coefficient, it was observed that the proposed hybrid model, incorporating decomposition, exhibited a remarkable increase of 31.81% compared to the standalone Meta-ELM model.The proposed hybrid CEEMDAN-Meta-Kernel-ELM approach has successfully enhanced the reliability of electronic monitoring data forecasting. Consequently, this approach has outperformed both standalone Meta-ELM and other hybrid model approaches, underscoring its superiority in accuracy and effectiveness. Thus, based on the findings, it is envisaged that the management and planning of electronic monitoring systems can be conducted with increased sensitivity and precision, utilizing data-driven approaches.

This model can be applied to other justice forecasting problems, such as crime prediction. Furthermore, the applicability of the proposed approach can be explored in various domains, such as renewable energy forecasting problems, load forecasting, econometric forecasting, and other related areas. Future studies on data forecasting will incorporate meta-heuristic approaches in combination with artificial intelligence methods to investigate potential advancements in performance.

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