PROCEEDINGS OF
INTERNATIONAL CONFERENCE ON ADVANCED TECHNOLOGIES
https://proceedings.icatsconf.org/
11th International Conference on Advanced Technologies (ICAT'23), Istanbul-Turkiye, August 17-19, 2023.

Prediction of Sleep Health Status, Visualization and Analysis of Data

Yavuz Selim Taspinar [1], Ilkay Cinar [2]

[1] *Department of Transport and Traffic Services, Doganhisar Vocational School, Selcuk University*
Konya, Türkiye
ytaspinar@selcuk.edu.tr

[2] *Department of Computer Engineering, Technology Faculty, Selcuk University*
Konya, Türkiye
ilkay.cinar@selcuk.edu.tr

***Abstract*— Sleep, as an indispensable element of human life, is accepted as one of the main sources of health, vitality and productivity. There are many factors that affect sleep health. Stress level, irregularity of sleep patterns and excessive use of technological devices can be given as examples. Sleep health can be determined by analyzing various variables about sleep. Sleep health can be determined by using these variables with machine learning methods. For this purpose, a dataset containing 374 rows of data and 13 features was used in this study. Sleep disorder conditions can be classified as None, Sleep Apnea, and Insomnia using 12 features. Random Forest (RF), Support Vector Machine (SVM), Logistic Regression (LR) and k Nearest Neighbor (kNN) methods were used for classification. Classification success was 91.66% from the RF model, 90.27% from the SVM model, 90.27% from the LR model and 87.50% from the kNN model. In order to analyze which feature is more effective in classification processes, box plot and correlation analysis methods were used. As a result of the analyzes, it was determined that the body mass index has the greatest effect on the determination of sleep disorder.**

***Keywords*— Machine learning, Sleep quality, Sleep Disorder, Correlation, Analysis**

I. Introduction

Sleep quality is extremely important for human health and general quality of life. Sleep is a process in which the body re-energizes physically and mentally, cells are repaired and brain functions are regulated. Sleep quality affects physical, mental, emotional and cognitive functions. For example, insufficient sleep can weaken the immune system and increase the risk of contracting infections. It also affects many physical health parameters such as weight control, heart health and diabetes. Poor quality sleep can lead to problems such as depression, anxiety and stress [1]. Sleep quality is one of the biggest factors that directly affect the functions of the brain. Insufficient sleep affects the brain's ability to process, organize, and store information. In addition, a good sleep increases the energy level and increases the capacity to perform daily activities. Along with this, an increase is observed in mental performance [2]. With quality sleep, the repair and growth of body cells can be carried out in a healthy way. Considering all these, it can be said that a good sleep quality increases the overall quality of life. For these reasons, paying attention to sleep quality and trying to get enough, uninterrupted and deep sleep significantly affects general health and quality of life. Sleep patterns, environmental factors and internal factors are the parameters used to determine sleep quality [3].

Today, rapid changes in the lifestyles of individuals have brought many factors that negatively affect the quality and quantity of sleep. Sleep is a fundamental requirement for human health and well-being, and insufficient or poor quality sleep can have profound effects on physical, mental and emotional health. The restorative functions of sleep cover a wide spectrum, from strengthening the immune system to regulating cognitive functions. Therefore, objectively evaluating and monitoring the sleep quality of individuals has become an important task for healthcare professionals [4].

While traditional sleep assessment methods rely on subjective questionnaires, this approach has limitations. Individuals' reporting of their own sleep experiences is based on subjective factors and memory, and is far from providing an objective analysis. At this point, machine learning techniques come to the fore as a promising tool to measure sleep quality in an unbiased and sensitive manner. Machine learning offers a new approach to sleep quality assessment, thanks to its ability to analyze large datasets and identify patterns. Data obtained through sensors can include important parameters such as individuals' sleep patterns, deep sleep stages, wake times, and even respiratory quality. When these data are processed with machine learning algorithms, it is possible to evaluate an individual's sleep quality more objectively and comprehensively [5].

To evaluate sleep quality with machine learning methods, the following steps are followed, respectively. In the data collection and preprocessing step, data that can be used to evaluate sleep quality are collected. These data include sleep quality parameters such as individuals' sleep patterns, waking times, REM and deep sleep stages. This data can be obtained through sleep monitors, portable devices and sensors. The collected data should be organized first and cleaned with preprocessing steps (such as lack of data, noise, outliers) when necessary [6]. A number of machine learning algorithms can be used to evaluate sleep quality during the selection phase of machine learning algorithms. These algorithms can include support vector machines (SVM), decision trees, random forests, neural networks, and deep learning models. The algorithm to be chosen is determined depending on the data type, sample size and target. During the training and model development phase, the data set is used to train machine learning algorithms. In the training phase, the algorithm learns patterns and relationships in the data. The model trained in the model validation and evaluation phase is tested on the validation data and its performance is evaluated. The success of the model is evaluated using different metrics (eg accuracy, sensitivity, specificity, F1 score) [7].

In the literature, there are studies on sleep quality, sleep health and the effects of these conditions on human life. A study of 1600 university students examined the prevalence and associated factors of sleep disorders. Advanced machine learning techniques and logistic regression were used to evaluate predictors of sleep quality. The study found a 70% prevalence of poor sleep quality. The random forest model provided 74% accuracy. While age and tea consumption were determined as protective factors; electronic use, headache, illness, and neck pain were found to be risk factors [8]. In another study, a model was presented to evaluate sleep quality based on the measurements of the actigraph used in an experiment on 22 subjects. Objective indicators of the actigraph include parameters such as time spent in bed, duration of sleep, number of awakenings, and duration of awakening. The resulting classification model was evaluated by various machine learning methods and a satisfactory accuracy rate of 80% to 86% was obtained. The results of the study have the potential to be used in areas such as the treatment of sleep disorders, the development and design of new systems for the assessment and monitoring of sleep quality, and the improvement of existing electronic devices and sensors [9].

Based on this information, the aim of this article is to examine in detail how machine learning techniques can be used to determine sleep quality. In the study, the following steps were carried out to determine sleep quality:

• A numeric dataset containing 13 features and 374 rows of data is used.

• Four different classification models were used to classify the data.

• Confusion matrix for each model was used to analyze the classification results in detail.

• Performance metrics of the models were calculated using the confusion matrix data.

• The ROC curves and learning levels of the classification models were analyzed.

The contributions of the study to the literature can be listed as follows:

• With machine learning methods, sleep quality analysis and classification will help in early diagnosis of sleep disorders and disorders such as sleep apnea.

• Machine learning algorithms will be able to provide personalized treatment and sleep management recommendations by analyzing individual sleep data.

• Large amounts of sleep data can help us understand the relationships between people's sleep habits, lifestyle factors, and health outcomes.

• Machine learning can be used to monitor the impact of a particular treatment or intervention on a patient's sleep quality. This can provide more information to clinicians to evaluate the efficacy of treatment and make adjustments as needed.

In conclusion, the potential of machine learning methods in sleep quality assessment offers an exciting opportunity to overcome the limitations of traditional methods and gain clearer and more comprehensive information about the sleep health of individuals. This article aims to contribute to the discovery of new approaches at the critical intersection of sleep quality and technology.

II. Material and Methods

A. *Sleep Health and Lifestyle Dataset (SHLD)*

SHLD has 374 rows of data and 13 features. 12 of 13 features are parameters that affect sleep quality. The 13th feature is the class feature that is desired to be estimated using other features. The class property contains three variables [10]. Insomina, None, and Sleep Apnea. The features and explanations in the dataset are given in Table 1.

TABLE I
Descriptions of Features in SHLD

Features	Descripton
Gender	The gender of the person (Male/Female).
Age	The age of the person in years.
Occupation	The occupation or profession of the person.
Sleep Duration (hours)	The number of hours the person sleeps per day.
Quality of Sleep (scale: 1-10)	A subjective rating of the quality of sleep, ranging from 1 to 10
Physical Activity Level (minutes/day)	The number of minutes the person engages in physical activity daily.
Stress Level (scale: 1-10)	A subjective rating of the stress level experienced by the person, ranging from 1 to 10.
BMI Category	The BMI category of the person (e.g., Underweight, Normal, Overweight).
Blood Pressure (systolic/diastolic)	The blood pressure measurement of the person, indicated as systolic pressure over diastolic pressure.
Heart Rate (bpm)	The resting heart rate of the person in beats per minute.
Daily Steps	The number of steps the person takes per day.
Sleep Disorder	The presence or absence of a sleep disorder in the person (None, Insomnia, Sleep Apnea).

B. *Random Forest (RF)*

Random forest is a widely used algorithm in the field of machine learning. This method is an ensemble learning technique in which many decision trees come together to form a model. Random forest can be used to solve classification and regression problems. This method is used to determine and predict the importance of features in the data set. The random forest creates many decision trees using different subsets of the dataset. Each tree is trained on randomly selected features and combined their results to make a prediction. One of the advantages of the random forest is its ability to reduce noise in the dataset. It can also perform well on large datasets and reduce the overfitting problem. The random forest can also take advantage of its parallel processing capabilities, making it work quickly and effectively. The random forest method is used in a variety of industries. For example, random forest method is used in fields such as medicine, finance, marketing and image processing [11].

C. *Support Vector Machine (SVM)*

Support vector machines (SVM) is an algorithm that provides solutions to classification and regression problems in the field of machine learning. By representing data points in a space, SVM aims to find a hyperplane separating these points. In classification problems, SVM is used to separate data points into two or more classes, while in regression problems it is used to estimate the relationship between data points. This algorithm aims at maximum marginal discrimination in classification problems. Margin refers to the largest gap between classes, and SVM strives to maximize this gap. Also, thanks to the ability to move data points to high-dimensional spaces using kernel functions, it is possible to achieve better results on more complex datasets. One of the key advantages of SVM is its robustness to noise in the dataset. In addition, SVM can offer effective performance even on small datasets and has the ability to reduce overfitting. It can also be used to solve multi-class classification problems. Support vector machines have a wide range of uses in a variety of industries. For example, the SVM method has been successfully used in areas such as image recognition, text classification, bioinformatics and financial forecasting [12].

D. *Logistic Regression*

Logistic regression is a statistical modeling method used to solve classification problems in the field of machine learning. This method is used to predict the relationship of a dependent variable (class label) with one or more independent variables. Its main purpose is to estimate the outcome as a probability value. Especially in classification problems, logistic regression is used to separate data points into two or more classes. Logistic regression uses the sigmoid function, also called the logistic function. This function converts the input values to a probability value between 0 and 1. This probability value expresses the predicted probability of the class label. In addition, logistic regression uses an optimization algorithm to determine the weights and the threshold value of the independent variables in the training dataset. These weights and the threshold provide the classification capability of the logistic regression model. Logistic regression can be used in many different industries. For example, logistic regression method is frequently used in fields such as marketing analysis, medical research, risk assessment and social sciences [13].

E. *k Nearest Neighbor (kNN)*

kNN is an algorithm that offers solutions to classification and regression problems in the fields of machine learning and data mining. This algorithm creates a model in which data points are located in a space. In the case of classification, it browses the classes of its nearest neighbors to determine the class of a data point. In the case of regression, it uses the values of its nearest neighbors to derive the estimated value of a data point. The k-NN algorithm has a simple and understandable structure. It usually calculates the distance between data points using metrics such as the Euclidean distance or the Manhattan distance. The k value determines the number of neighbors. For example, if k=3, the 3 nearest neighbors are looked at to determine the class or value of a data point. One of the advantages of the k-NN algorithm is that the training process is fast and simple. In addition, it is easily applicable to new data points and has a flexible structure. However, its performance may degrade on large datasets or high-dimensional data. It can also be sensitive to noise and outliers in the dataset. The k-NN algorithm finds use in various industries. For example, the k-NN algorithm has been successfully used in disease diagnosis, image processing projects, marketing strategies and recommendation systems in the medical field [13].

F. *Confusion Matrix*

The complexity matrix (Confusion Matrix) is a table used to evaluate the performance of a classification model [14, 15]. The complexity matrix visualizes the correct and incorrect classifications of the model by comparing the predictions of the model with the actual class labels [16]. A two-class complexity matrix is shown in Table 2.

TABLE III
TWO CLASS CONFUSION MATRIX

CONFUSION MATRIX		ACTUAL CLASS	
		CLASS 1	CLASS 2
PREDICTED CLASS	CLASS 1	TP	FP
	CLASS 2	FN	TN

The complexity matrix usually includes four main components [17, 18]:

True Positive (TP): The number of samples that the model correctly predicts as positive.

True Negative (TN): The number of samples that the model correctly predicts as negative.

False Positive (FP): The number of samples that the model falsely predicted to be positive.

False Negative (FN): The number of samples that the model incorrectly predicted to be negative.

G. *Performance Metrics*

Performance metrics are calculated using the values on the complexity matrix. Performance metrics can be easily calculated using these values [19]. The formulas required to calculate the performance metrics used in the study are given in Table 3.

TABLE IIIII
PERFORMANCE METRICS

Metrics	Formulas
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
F1 Score	$2*\frac{PRE*RCL}{PRE+RCL}$
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$

Accuracy: The percentage of samples classified as correct [20].

Precision: It is a measure of how accurately it is predicted from all classes [21].

Recall: It is a metric that indicates the rate of correctly predicted positive of samples that should be predicted as positive [22].

F1 Score: It is the harmonic mean of the ratio of true positive values (recall) and precision (precision). It is a measure of how well classifiers perform [23].

ROC Curve: A graph used to summarize the performance of classifiers over all possible values. It is created by plotting the Ratio of True Positive Values (Sensitivity) (x-axis) versus the Ratio of False Positive Values (Specificity) (y-axis). The ROC Curve is used to generate a Sensitivity / Specificity report [24].

III. EXPERIMENTAL RESULTS

Classification processes were performed using RF, SVM, LR and kNN methods using the Sleep Health and Lifestyle Dataset (SHLD). In classification processes, k-fold cross validation was used and the k value was determined as 10. In the dataset, each feature has a correlation relationship with each other and with the class feature. In other words, while some features contribute highly to classification, some features contribute little. However, in real-world problems, experts evaluate sleep status by considering all values. For this reason, finding effective features is important in theory, but in practice it is done according to expert opinion. The heatmap showing the relationship between the features in the dataset is shown in Fig. 1.

The distribution of the features in the dataset relative to each other can show the behavior of the features relative to each other. Boxplots showing the distributions according to gender-sleep duration features in Fig. 2, sleep duration-bmi in Fig. 3, and sleep duration-sleep disorder features in Fig. 4 are shown.

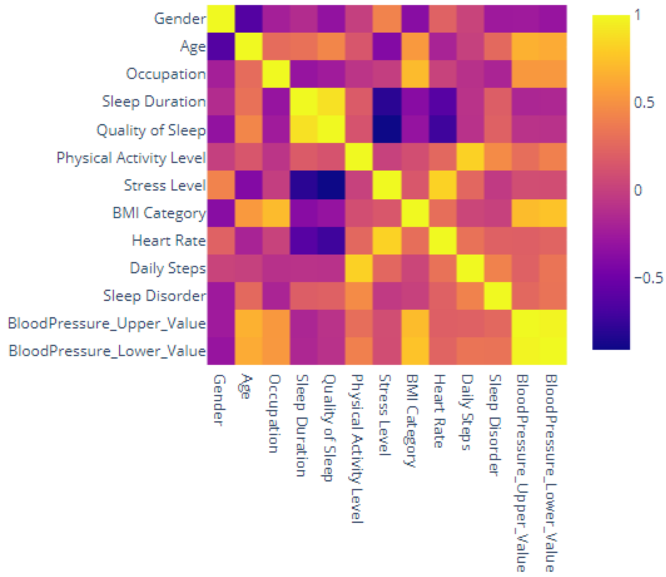

Fig. 1 Heatmap of dataset features

Fig. 2. Boxplot of gender-sleep duration

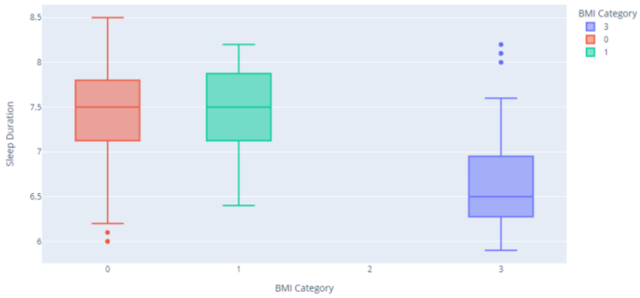

Fig. 3. Boxplot of sleep duration-bmi

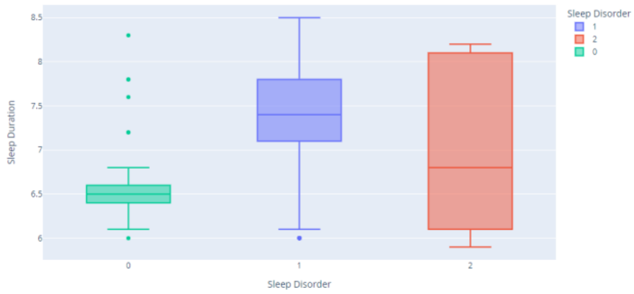

Fig.4.. Boxplot of sleep duration-sleep disorder

Different confusion matrices were obtained in the classifications made with machine learning models. The conufison matrix obtained from the RF model is shown in Table 4. The confusion matrix obtained from the SVM model is shown in Table 5, the confusion matrix obtained from the LR model is shown in Table 6 and the confusion matrix obtained from the kNN model is shown in Table 6.

TABLE 4. CONFUSION MATRIX OF RF

RF CONFUSION MATRIX		ACTUAL CLASS		
		Insomnia	None	Sleep Apnea
PREDICTED CLASS	Insomnia	64	3	6
	None	8	213	6
	Sleep Apnea	5	6	66

TABLE 5. CONFUSION MATRIX OF SVM

SVM CONFUSION MATRIX		ACTUAL CLASS		
		Insomnia	None	Sleep Apnea
PREDICTED CLASS	Insomnia	63	7	5
	None	10	207	5
	Sleep Apnea	4	5	68

TABLE 6. CONFUSION MATRIX OF LR

LR CONFUSION MATRIX		ACTUAL CLASS		
		Insomnia	None	Sleep Apnea
PREDICTED CLASS	Insomnia	62	5	4
	None	10	207	5
	Sleep Apnea	5	7	69

TABLE 7. CONFUSION MATRIX OF KNN

kNN CONFUSION MATRIX		ACTUAL CLASS		
		Insomnia	None	Sleep Apnea
PREDICTED CLASS	Insomnia	64	8	7
	None	9	204	12
	Sleep Apnea	4	7	59

When Table 4-7 is examined, it can be seen that the most successful model is RF. It can be seen that the model with the lowest success is the kNN model. It can be seen that the LR and SVM models have almost the same classification values. Performance metrics calculated using the confusion matrix data are shown in Table 8.

TABLE 8. PERFORMANCE METRICS OF ALL MODELS

	Accuracy	F1 Score	Precision	Recall
RF	91.66	91.66	91.65	91.66
SVM	90.27	90.27	90.25	90.26
LR	90.27	90.25	90.26	90.23
kNN	87.50	87.50	87.50	87.50

When Table 8 is examined, it is seen that the model with the highest classification success is RF. It is seen that the model with the lowest classification success is kNN. In other performance metrics, the highest values belong to the RF model and the lowest values belong to the kNN model. The ROC curves obtained as a result of training and testing these models are shown in Fig. 5.

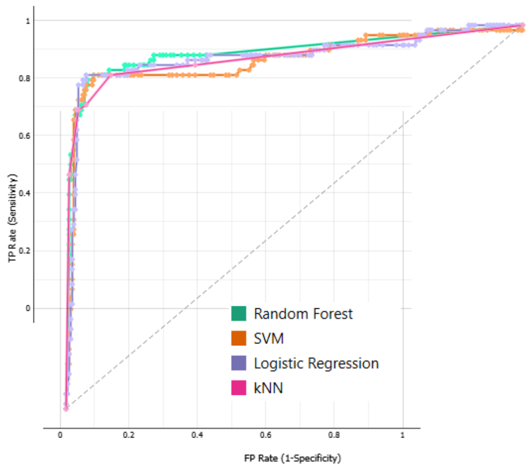

Fig. 5. ROC curve of all models

IV. CONCLUSIONS

By taking various measurements from people, information about sleep health can be obtained. As the measurement parameters increase, it may be difficult for experts to make decisions about sleep health. Machine learning methods can be used to predict sleep health. In this study, RF, SVM, LR and kNN methods were used to predict sleep health using sleep measurements. The success of the classification models in all of the data was also analyzed using the cross validation method. Confusion matrix was used to calculate the success of the models and other performance metrics. The performance metrics of the models were calculated using the data on this matrix. F1 Score, precision recall and accuracy performance metrics are used. Classification success was 91.66% from the RF model, 90.27% from the SVM model, 90.27% from the LR model and 87.50% from the kNN model. Among these models, it can be said that the RF model has the highest classification success.

Classification success can be increased by using different datasets and machine learning methods. By increasing the data in the dataset, the prediction of sleep health can be made with higher classification successes. It can be said that the models proposed in this study have a helpful feature for the expert. It is possible for people to see their sleep health by entering their own values by making a mobile application or a web application.

ACKNOWLEDGMENT

The heading of the Acknowledgment section and the References section must not be numbered.

REFERENCES

[1] M. Fabbri, A. Beracci, M. Martoni, D. Meneo, L. Tonetti, and V. Natale, "Measuring subjective sleep quality: a review," *International journal of environmental research and public health,* vol. 18, no. 3, p. 1082, 2021.

[2] F. Wang and É. Bíró, "Determinants of sleep quality in college students: A literature review," *Explore,* vol. 17, no. 2, pp. 170-177, 2021.

[3] D. Kocevska, T. F. Blanken, E. J. Van Someren, and L. Rösler, "Sleep quality during the COVID-19 pandemic: not one size fits all," *Sleep medicine,* vol. 76, pp. 86-88, 2020.

[4] J. Kohyama, "Which is more important for health: sleep quantity or sleep quality?," *Children,* vol. 8, no. 7, p. 542, 2021.

[5] A. J. Scott, T. L. Webb, M. Martyn-St James, G. Rowse, and S. Weich, "Improving sleep quality leads to better mental health: A meta-analysis of randomised controlled trials," *Sleep medicine reviews,* vol. 60, p. 101556, 2021.

[6] M. Bergmann, L. Tschiderer, A. Stefani, A. Heidbreder, P. Willeit, and B. Hoegl, "Sleep quality and daytime sleepiness in epilepsy: Systematic review and meta-analysis of 25 studies including 8,196 individuals," *Sleep Medicine Reviews,* vol. 57, p. 101466, 2021.

[7] B. Karasulu, F. Yücalar, and E. Borandag, "İnsan kulağı görüntüleri kullanarak cinsiyet tanıma için derin öğrenme tabanlı melez bir yaklaşım," *Gazi Üniversitesi Mühendislik Mimarlık Fakültesi Dergisi,* vol. 37, no. 3, pp. 1579-1594, 2022.

[8] A. A. Alghwiri, F. Almomani, A. A. Alghwiri, and S. L. Whitney, "Predictors of sleep quality among university students: the use of advanced machine learning techniques," *Sleep and Breathing,* vol. 25, pp. 1119-1126, 2021.

[9] O. V. Bitkina, J. Park, and J. Kim, "Modeling sleep quality depending on objective actigraphic indicators based on machine learning methods," *International Journal of Environmental Research and Public Health,* vol. 19, no. 16, p. 9890, 2022.

[10] *Sleep Health and Lifestyle Dataset*. [Online]. Available: https://www.kaggle.com/datasets/uom190346a/sleep-health-and-lifestyle-dataset

[11] Y. S. Taspinar, I. Cinar, and M. Koklu, "Prediction of computer type using benchmark scores of hardware units," *Selcuk University Journal of Engineering Sciences,* vol. 20, no. 1, pp. 11-17, 2021.

[12] B. Kishore *et al.*, "Computer-aided multiclass classification of corn from corn images integrating deep feature extraction," *Computational Intelligence and Neuroscience,* vol. 2022, 2022.

[13] M. Koklu and Y. S. Taspinar, "Determining the extinguishing status of fuel flames with sound wave by machine learning methods," *IEEE Access,* vol. 9, pp. 86207-86216, 2021.

[14] M. Dogan, Y. S. Taspinar, I. Cinar, R. Kursun, I. A. Ozkan, and M. Koklu, "Dry bean cultivars classification using deep cnn features and salp swarm algorithm based extreme learning machine," *Computers and Electronics in Agriculture,* vol. 204, p. 107575, 2023.

[15] E. Borandag, "Software Fault Prediction Using an RNN-Based Deep Learning Approach and Ensemble Machine Learning Techniques," *Applied Sciences,* vol. 13, no. 3, p. 1639, 2023.

[16] Y. S. Taspinar, M. Koklu, and M. Altin, "Fire Detection in Images Using Framework Based on Image Processing, Motion Detection and Convolutional Neural Network," *International Journal of Intelligent Systems and Applications in Engineering,* vol. 9, no. 4, pp. 171-177, 2021.

[17] A. Feyzioglu and Y. S. Taspinar, "Beef Quality Classification with Reduced E-Nose Data Features According to Beef Cut Types," *Sensors,* vol. 23, no. 4, p. 2222, 2023.

[18] Y. S. Taspinar, "Light weight convolutional neural network and low-dimensional images transformation approach for classification of thermal images," *Case Studies in Thermal Engineering,* vol. 41, p. 102670, 2023.

[19] Y. S. Taspinar and M. Selek, "Object recognition with hybrid deep learning methods and testing on embedded systems," *International Journal of Intelligent Systems and Applications in Engineering,* vol. 8, no. 2, pp. 71-77, 2020.

[20] Ö. Özaltin and Ö. Yeniay, "Detection of monkeypox disease from skin lesion images using Mobilenetv2 architecture," *Communications Faculty of Sciences University of Ankara Series A1 Mathematics and Statistics,* vol. 72, no. 2, pp. 482-499, 2023.

[21] O. Ozaltin and O. Yeniay, "A novel proposed CNN–SVM architecture for ECG scalograms classification," *Soft Computing,* vol. 27, no. 8, pp. 4639-4658, 2023.

[22] R. Butuner, I. Cinar, Y. S. Taspinar, R. Kursun, M. H. Calp, and M. Koklu, "Classification of deep image features of lentil varieties with machine learning techniques," *European Food Research and Technology,* vol. 249, no. 5, pp. 1303-1316, 2023.

[23] Y. S. Taspinar, M. Koklu, and M. Altin, "Identification of the english accent spoken in different countries by the k-nearest neighbor method," *International Journal of Intelligent Systems and Applications in Engineering,* vol. 8, no. 4, pp. 191-194, 2020.

[24] Y. S. Taspinar, M. Koklu, and M. Altin, "Classification of flame extinction based on acoustic oscillations using artificial intelligence methods," *Case Studies in Thermal Engineering,* vol. 28, p. 101561, 2021.