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Preface

The publication process of the ‘Inspiring Technologies and Innovations (INOTECH)’ journal is continuing with the decision numbered 261 taken at the session of the Senate of Kastamonu University dated 2.12.2021 and numbered 26, and with the coordination of Kastamonu University Technology Transfer Office.

Our journal named ‘Inspiring Technologies and Innovations (INOTECH), which is a pioneer because it prioritizes R&D and innovation issues in multidisciplinary fields, is a peer-reviewed, open access, free publication policy and periodical research journal by Kastamonu University twice a year.

Aiming to develop in the way of presenting qualified works to national and international readers with the principle of scientific publishing, this first issue of our journal includes 5 original research and 1 review research articles from different disciplines and research fields.

We would like to thank all the academicians who contributed by sending their works, and all the referees who contributed in the evaluation process of these works;

We hope that the interest and support for our journal from the national and international community
will increase.

Regards.

Prof. Dr. Alperen KAYMAKÇI
Chief Editor

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Content

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Research Article

Investigation of the Morphological and Root Structure of the Arabic Language Structure Using Python

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ABSTRACT: In the last years, scientists in computer and software have made successful studies in almost every field. Especially in the classification and comparison of optimization algorithms, metaheuristic optimization techniques can be generally classified as population-based and trajectory-based methods. These algorithms are quite suitable for high-dimensional problems and exhibit strong discovery capabilities. The algorithms use a single solution and iteratively improve it based on mathematical models or heuristics. Arabic is a language of derivation with a very rich derivational morphology, with virtually all words originating from roots through patterns. It is a language with numerous inflections and a complicated morphological structure. Arabic plurals used in modern Arabic are listed. Arabic is becoming a significant topic because of applications for information retrieval and natural language processing. There are two types of Arabic plurals: regular and irregular. The standard form also includes masculine and feminine versions. Stemming is a method used in information retrieval to differentiate between single and plural nouns by eliminating the corresponding affixes from words. In this study, we describe a technique that does not rely on stemming to recognize Arabic plurals. Based on the threefold relationship between word, root, and pattern, we utilize both the word and the pattern to find the correct root and the pattern used to define the type of plural. The algorithm has only been provided the fundamental patterns of plurals, whether regular or irregular; the remaining patterns are constructed programmatically to add the appropriate plugins for each type of plural. Finally, since irregular inclusion and humiliation are not governed by direct laws, we get positive outcomes in both cases. In the situation of irregular inclusion and humiliation, we are largely satisfied. Although generally faster, these methods may experience problems such as premature convergence or being stuck in local optima. Recent research has focused on improving existing algorithms by hybridization, parameter tuning, and incorporating additional mechanisms such as chaos theory and adversarial learning.

KEYWORDS: Pyhton arabic plurals, morphology, root, optimization.

1. INTRODUCTION

The most common problem with metaheuristic algorithms is user-defined parameters. Mathematical models using random numbers negatively affect the global optimum convergence. The LM trap must be managed between exploration and exploitation tendencies to prevent premature convergence. There are many options for working with GM-capable and successful SI and EA algorithms. Birds engage in social interactions to obtain sufficient food. Each individual in the flock represents a solution. To update their position in the search space, for example in PSO, the current speed is multiplied by the current position. The best solution so far has been obtained by the PSO algorithm and it improves with each iteration. The global best position can only be reached by the group members. Subfield of artificial intelligence (AI) called Natural Language Processing (NLP) is focused on understanding and modifying human languages. Each individual human natural language has a unique collection of rules and syntaxes that set it apart from other languages. Writing, translating, and even speaking natural language is challenging since these languages contain inflectional, which adds to the confusion [1]. Humans can interpret meaning from context and have feelings, while computer algorithms and programs struggle to do this and make mistakes [2]. In order to build and improve their job reach tools and application activities in this field, researchers are continually working on these projects. Over time, NLP has developed into a growing field. Examples of NLP fields that have existed and are still in existence include machine translation, text description, sentiment analysis, word segmentation, information retrieval, and text categorization [3]. In NLP applications, the Morphological Analyzer is a significant module that recognizes and examines the structural structure of words in a specific language [6]. The process of generating a new word from an existing one is referred to as morphology. It is common for morphological analysis to be challenging, computationally demanding, and inherently parallel [7]. Arabic information retrieval systems' major objective is to find and retrieve Arabic documents from databases that are crucial to a particular query. In these systems, retrieving documents is done by comparing query and index terms for similarity. Arabic numbers come in solitary, dual, and plural forms. Consequently, the Arabic plural starts at three. Arabic plurals can be either regular or broken (irregular) [8]. Light stemmers swiftly change irregular plurals (broken plurals), which contain infixes in addition to prefixes and suffixes, into their single forms. Regular plurals can be separated from irregular plurals by the addition of a suffix, which is a collection of letters at the end of a word. While broken plurals are problematic, it can be challenging to identify them because of their intricate patterns [9]. We suggest a technique in this paper that can distinguish between regular and irregular plurals without eliminating any suffixes, Instead, the approach makes advantage of the pattern to identify the word's root before determining its morphology, which in this case is plural.

1.1. Arabic Language Overview
Arabic contain Twenty-eight letters written from right to left make up the word, which can be increased to ninety by including more shapes [10]. Only a small portion of native Arabic words are derived from four, five, or six letter roots, the majority of which are formed from three consonant letters (triliteral roots) [11,12]. It has been challenging to locate standard Arabic text mining algorithms and techniques. Verbs, nouns, and particles are the three divisions of the Arabic language. Arabic has short vowels that are not letters, often known as diacritics. These vowels make grammar checking and root extraction simpler while also reducing the ambiguity of a word's meaning [13]. These patterns are made by attaching affixes to the roots and can be seen as models that adhere to Arabic grammatical standards. To extract various grammatical applications, such as possessives, plurals, definite forms, gender, and so forth, additional affixes might be introduced [14]. Arabic is a language of several roots and both nouns and verbs are descended from a series of robots. The process of "root extraction," also known as "stemming," is a means to locate or recognize the root or stem of any Arabic word [15].

1.2. Arabic Morphology
Arabic's morphological representation is quite intricate due to morphological events like agglutination. Depending on where they are in the word (beginning, middle, end, and separate), letters take on distinct shapes [17]. Morphological analysis is a crucial stage in language processing because of Arabic's intricate morphological structure. It appears that morphology has persuaded traditional Arabic grammarians to classify words only into verbs, nouns, prepositions, and particles. Almost all words in Arabic are formed from roots applying patterns, making it essentially a derivational language with an extremely rich derivational morphology. The bulk of Arabic words have three-letter roots as their foundation. [16, 18]. Arabic is a morphologically complicated language. It is possible to define short vowels, consonantal doubling, and the morpheme using optional diacritics. The absence of these diacritics and the rich morphology of the language lead to a considerable degree of certainty, several Arabic letters are frequently wrongly spelled. Because of these complexities, the Arabic language poses a substantial barrier for NLP [4,19, 20, 21].

1.3. Plurality in Arabic
Arabic numbers come in three different varieties: singular, dual, and plural. As a result, the Arabic plural starts at three. Arabic distinguishes between regular and irregular (broken) plurals [8]. The most exciting case is the one involving the broken plural because it requires a lot of time and effort to solve. There are no set rules for how to produce a broken plural or how to recognize one (such as adding or removing letters from the single form). There are several ways to carry out these processes. Each strategy has advantages and disadvantages [5, 22]. The elimination of affixes, the application of grammatical rules, or even the usage of dictionaries is a few of these strategies.

1.4. Arabic Regular Plural
The Arabic regular plural is formed by adding no additional letters to the stem. It's also important to remember that the pattern of an Arabic word consists of three letters, which are typically represented by the letters "ع" "ف" and "ل" Arabic nouns and adjectives can be classified as either masculine or feminine. Because of this, plurals are formed using various inflectional suffixes with little to no internal shift [8]. There are two types of this plural component, as follows:

1.5. Arabic Masculine Regular Plural
The usable nouns in male standard plurals are the sensible masculine proper nouns, whose bases do not terminate in a vowel letter, and the sensible masculine adjectives. The masculine regular form gains the suffixes "ون" or "ين" [8,9].

1.6. Arabic Feminine Regular Plural
This common Arabic plural can be used to refer to a broad variety of noun categories, including both human and nonhuman individuals, as well as adjectives. The typical feminine plurals are formed with the suffix "ات"; it should be noted that when the stem ends in the letter "," the suffix takes its place [8,9].

1.7. Arabic Irregular Plural
In Arabic, there are a number of specific requirements that must be followed in order to construct irregular plurals, which lack a clear structure [8]. It's important to note that the Arabic language has a high degree of inflectional structure, with more than 85% of all words having trilateral origins. Arabic verbs and nouns are typically derived from a group of roots [23]. Broken plurals make up 10% of documents in large Arabic corpora, while plurals make up 41% [9]. Broken plural identification is a serious issue for light-stemming algorithms created for applications like information retrieval. Arabic has tight rules for how to produce irregular plurals, which lack a clear structure [8]. A root is the most fundamental word in phonetics, used as a base for the addition of suffixes or affixes to produce various derivatives like verbs, adjectives, and nouns. It's important to note that approximately 85% of Arabic words have trilateral origins, making it a highly inflectional language [7].

2. MATERIAL AND METHOD

A few studies have concentrated solely on the Arabic plural, despite the fact that a great deal has been done in the area of Arabic morphological analysis and generation using a range of techniques and at various levels of linguistics. These few studies focus on the removal of singular nouns from their plural forms as well as the derivation of the plural from the singular or the base. In this section, we discuss a few of these studies in order to better grasp their methods for morphological study of Arabic as a whole. In the Table 1, we will discuss some of the prior studies on the subject of identifying verbs in various ways and at various periods in the rest of this section of the study.

Table 1. Plural Recognizing Related Works

Years	Author(s)	Discussion
2013	Alexis Amid Neme and Eric Laporte	They proposed a model that is implemented and takes broken plurals into account. The model uses a lexicon of terms to do direct morphological analysis of Arabic text rather than using morphophonological criteria. by defining vowel quantity and neglecting vowel quality to streamline the taxonomy of singular patterns. Without deep roots or morphophonological or orthographical principles, root alternations and orthographical variants are recorded independently from patterns and in a factual manner [24].
2014	Abduelbaset Goweder, Massimo Poesio, Anne De Roeck and Jeff Reynolds	They show that irregular plural recognition in modern standard Arabic is a difficult problem for information retrieval and language engineering applications. They developed a number of methods for detecting irregular plurals and tested them. The irregular plural detection component was integrated into a new light-stemming algorithm that conflates both regular and irregular plural with their singular forms [16].
2016	Ali Shafah, Abduelbaset Goweder, Samira Eshafah and Ahmed Rgibi	They proposed a method for identifying broken plurals in Arabic without the need for stemming. they used the decision tree framework (WEKA J48) to construct a classifier (model). An unknown test set is used to evaluate the constructed classifier. The findings show that a promising broken plural recognizer for natural language processing applications could be developed and implemented [9].

The field of Arabic language morphology has seen a wide range of studies and analysis. Many of these studies employ either applying either grammatical rules or eliminating affixes, or even using both of them together. The research methods and algorithms used to create a morphological analyzer are different. The majority of research in the field of plural has concentrated on irregular plural. We will present an approach in this paper that uses the pattern to find the root and then determine the form of plural from the pattern used. In This paper, we introduce a technique that can extracts, roots directly without any affix removal, it just matches the words to extract its root by a pattern with the same number of letters, and we will discuss in more detail the ideas of our algorithms in section four.

3. RESULTS AND DISCUSSION

Regular and irregular Arabic plurals are the two categories. The common form contains both masculine and feminine forms. A crucial and challenging issue that needs to be solved is the detection of plurals. In this work, we have presented a method for identifying Arabic plurals without removing affixes or using grammar rules, but rather by relying on the three-way relationship between word, root, and pattern to determine the word's structure. Linguists consult the Holy Qur'an and take the Qur'an's requirements for proper grammar into consideration since they believe that the Qur'an is the language of the book. With 6144 words, Surat Al-Baqarah is the largest surah in the Qur'an, thus we used it to test our technique. Although the letters of the Noble Qur'an include diacritical marks, our algorithm works with letters without them since the Arabic used today, whether in printed or electronic books or even online pages, lacks diacritical marks. An algorithm for detecting Arabic plural was presented. In this method, the pattern is used to extract the root, and the second step is to determine how to determine the plural from the pattern that was used to extract the root. After the text has been preprocessed, which removes all extraneous words from the original text such as stop words, vowels, digits, and non-text characters, these two processes are carried out. The fundamental concept is to consider the connections between the three components, word, pattern, and root. In our suggested approach, we have utilized these relations and translated them. The steps of this method are shown in Figure 1.

```
Algorithm RecognizeArabicPlular(ArabicText)
    // input text as Arabic Words.
    // output: List of Arabic Plular.
  for Patt in PatternsList:
      Root = ‘’
      for each char in Patt:
          if char in [‘F’,’A’,’L’]:
             root = root + char
          end if
      end for
      word = ‘’
      for each char in Patt:
          if char in [‘F’,’A’,’L’]:
             word = word + root(char)
          end if
      end for
      if word == WORD:
          print(‘word is Plular frm type Patt’)
          exit for
      end if
    end for
end Algorithm
```

Figure 1. Algorithm to identify Arabic plural

The basic patterns for plurals as well as affixes that can be added to these patterns have been provided to the algorithm. The algorithm itself will produce all additional patterns that are employed in opposition to all words. The patterns used to identify masculine regular plural are shown in Tables (2), (3), and (4), respectively, whereas the patterns for irregular plural are shown in Table (3).

Table 2. Patterns for masculine regular plural

اتفعل	فاعل	مفعل
استفعل	فعال	مستفعل
افتعل	فعل	يتفعل
افعل	فعلان	يستفعل
تتفعل	فعلي	يفتعل
تفاعل	فعول	يفعل
تفعال	فعيل	
تفعل	متفعل	

Table 3. Patterns for feminine regular plural

افتعال	فعال	متفعل
افعال	فعل	مفاعل
تفاعل	فعلاو	مفتعل
تفعيل	فعلي	مفعل
فاعل	فعيل	مفعول

Table 4. Patterns for irregular plural

فعال	افعلاء	افوعلكم	فعلياكم	فعليهم
افعال	فعلهم	بفعليهم	فافعلنا	فعلوا
فعلة	افعالهم	افعلناكم	مفعلهم	فعلناهم
افعلنا	افوعلها	افعلوا	يفعلونهم	الفواعل
فعول	فعولها	فعلتكم	يفعلهم	بفعلهم
تفاعيل	مفاعيل	يفعلونكم	تفعلتم	الافعال
مفاعل	فعولهم	فعلتم	افعلاوهم	الفعايلة
فعلاء	افعالنا	بافتعالكم	فعلة	فافعلوا
فعلاءكم	افعالكم	فافعلوا	فعولكم	فعلتنا
فعالكم	الافعل	فعلونا	ليفتعلا	بفعلايهم

4. CONCLUSION

Morphology is a subfield of linguistics that studies the internal structure of words. It examines how affixation affects word creation as well as word origins and pattern characteristics. Case, gender, number, tense, person, mood, and speech are just a few of the properties that can be impacted by inflection [16]. The remainder 2133 words after excluding diacritics, numerals, stop words, and repeated words. There was a 98 percent recognition rate for the masculine regular plural, a 97 percent identification rate for the feminine regular plural, and a 90 percent identification rate for the broken plural. We did not use a dictionary or lexicon, and our whole process did not make use of any grammatical rules. One advantage of what we've done is that it processes data more slowly than other algorithms, which are frequently composed of intricate IF statements. We think that by mixing many algorithms simultaneously, we can get superior outcomes. For example, if we apply grammatical rules and use language dictionaries in our algorithm, we can achieve more accurate results.

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Research Article

Corn and Wheat Plant Identification on Radar and Optical Image Data

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ABSTRACT: In recent years, prediction, detection, and classification applications have been made in many fields such as agriculture, health, stock market, economy, cybersecurity, etc., in Machine Learning and Artificial Intelligence. These applications are user-friendly and provide fast, high-quality, and accurate results. The advancements in these fields have shown that machine learning and deep learning methods are very useful in classifying large and complex data, especially when human brain and physical power are insufficient. Today's findings suggest there have been promising studies using these models, focused on time- and cost-effective and high-quality products. These studies provide efficiency in agricultural areas, thereby guiding both farmers and policymakers. In addition, the development and widespread implementation of unmanned aerial vehicles (UAVs) accelerated the process of obtaining multispectral aerial images. With the combined use of these technologies and high-speed computer software and hardware for precise and high-quality production in agriculture, it was possible to determine plant species and increase product quality. In this study, a dataset consisting of radar and optical image data was used to classify corn and wheat crops cultivated in agricultural areas. Four different machine learning models, namely Decision Tree (DT), K-Nearest Neighbors (K-NN), Naive Bayes (NB), and Support Vector Machines (SVM), were trained and compared on the dataset consisting of 174 features from Winnipeg, Canada. The dataset has been divided into 80% for training and 20% for testing. According to the results, the SVM model performed the best with the highest accuracy (0.9998) and F1-Score (0.9996), while the NB model performed the worst accuracy (0.9895) and F1-Score (0.9835). The detection of wheat and corn crop types by processing radar and optical image data with machine learning models has shown that other crops in cultivated lands in the Southeastern Anatolia Project (GAP) region can be classified using the same method, which shows the importance of this study.

KEYWORDS: Machine learning, classification, multispectral aerial images, plant species.

ÖZET: Makine Öğrenmesi ve Yapay Zeka konularında son yıllarda tarım, sağlık, borsa, ekonomi, siber güvenlik vb. birçok alanda tahmin, tespit ve sınıflandırma uygulamaları yapılmıştır. Bu uygulamalar hızlı, kaliteli ve yüksek doğrulukta sonuç alınabilen kullanıcı dostu uygulamalardır. Bu alanlardaki gelişmeler, makine öğrenimi ve derin öğrenme yöntemlerinin, özellikle insan beyninin ve fiziksel gücün yetersiz kaldığı durumlarda, büyük ve karmaşık verilerin sınıflandırılmasında çok faydalı olduğunu göstermiştir. Günümüzde bu modellerin kullanıldığı, zaman ve maliyet etkin, yüksek kaliteli ürün odaklı umut verici çalışmalar yapılmıştır. Bu çalışmalar tarım alanında verimlilik sağlayarak gerek çiftçi gerek ise politika yapıcıları yönlendirmektedir. Ayrıca, insansız hava araçlarının (İHA) geliştirilmesi ve yaygın kullanımı, çok spektrumlu hava görüntülerinin elde edilme sürecini hızlandırmıştır. Tarımda hassas ve kaliteli üretim için bu teknolojiler ile yüksek hızlı bilgisayar yazılım ve donanımlarının birlikte kullanılmasıyla bitki türlerinin belirlenmesi ve ürün kalitesinin artırılması mümkün olmuştur. Bu çalışmada, tarım alanlarında yetiştirilen mısır ve buğday mahsullerini sınıflandırmak için radar ve optik görüntü verilerinden oluşan bir veri seti kullanılmıştır. Karar Ağacı (KA), K-En Yakın Komşular (K-EYK), Naif Bayes (NB) ve Destek Vektör Makineleri (DVM) olmak üzere dört farklı makine öğrenimi modeli, Kanada'nın Winnipeg kentinden alınan 174 özellikten oluşan veri kümesi üzerinde eğitilmiş ve karşılaştırılmıştır. Veri kümesi, eğitim için %80 ve test için %20 olarak ayrılmıştır. Sonuçlara göre, DVM modeli en yüksek doğruluk (0,9998) ve F1-Skoru (0,9996) ile en iyi performansı gösterirken, NB modeli en düşük doğruluk (0,9895) ve F1-Skoru (0,9835) performansını göstermiştir. Radar ve optik görüntü verilerinin makine öğrenmesi modelleri ile işlenerek buğday ve mısır ürün türlerinin tespit edilmesi, Güneydoğu Anadolu Projesi (GAP) bölgesindeki ekili arazilerde bulunan diğer ürünlerin de aynı yöntem kullanılarak sınıflandırılabileceğini göstermiş ve bu çalışmanın önemini ortaya koymuştur.

ANAHTAR KELİMELER: Makine öğrenmesi, sınıflandırma, multispektral hava görüntüleri, bitki türleri.

1. INTRODUCTION

With the acceleration of artificial intelligence research, machine learning methods have had many positive effects on human life. In recent years, products offered to end-users, such as AI-powered chatbots, smart robot vacuum cleaners, smart assistants, and autonomous cars, reveal today's technology and demonstrate the contemporary technology and importance of artificial intelligence. In particular, with the increased interest in autonomous technologies, many new technologies beneficial to humanity are being introduced in areas such as production, transportation, the defense industry, and agriculture. The backbone of these technologies involves machine learning models, and large datasets are processed.

On human interaction and socio-cultural impact, Altinel conducted a sentiment analysis study on social media using machine learning methods. Since classifying and analyzing the large amount of data generated by the ideas shared on these platforms would require a large workforce when done with human, it was determined that emotion analysis should be done with a number of existing algorithms. In this study, used five various datasets from various platforms and used four distinct algorithms for machine learning (K-NN, NB, RF, SVM) for each dataset, aiming to identify the most accurate model through performance comparison [1].

A dynamic Turkish sign language recognition [2] using machine learning models and a leap motion sensor was studied in order to facilitate the lives of deaf and hearing-impaired people by Demircioglu. The importance of this study was revealed by the communication difficulties experienced by hearing-impaired people in society, particularly in environments where they cannot understand sign language. Within the scope of this thesis, software that can run on a mobile device with a minimal size sensor and processor has been created, and solving this problem has been set as a goal. It is aimed at developing a highly efficient recognition system using machine learning methods [2].

On agricultural applications, Mucherino et al. concentrated on the implementation of data mining techniques in agriculture, noting that neural networks do not rank among the top ten data mining methods and that their applications in agriculture are limited [3]. Tabanlioglu et al. proposed the use of UAVs to monitor the productivity of large agricultural lands, as taking images from the ground is inefficient and time-consuming [4]. In this study, aerial images of agricultural lands in the GAP region were analyzed with image processing techniques, and color analysis was performed to control productivity in a computer environment. In addition, it is aimed to increase productivity and economic growth by suggesting that the most important development factor in this region is agricultural practices [4]. Rumpf et al. pointed out that the use of automated systems for the prompt identification of plant diseases are essential for precision in plant protection, and a study was conducted for prompt identification and differentiation of sugar beet problems with a SVM algorithm generated from hyperspectral plant image data [5]. Gumuscu et al. used K-NN, SVM, and DT classification algorithms to determine the planting date, taking into account the significant impact of planting dates on agricultural production. In the proposed method, meteorological data was used as input, and it was aimed to provide farmers with the correct planting date and to achieve higher yields. In order to reduce the number of features in the high-dimensional dataset, a genetic algorithm was used to eliminate the excessively high processing time and to improve the prediction performance [6]. Karadag et al. suggested that irrigation should be done by considering soil and climatic factors and pointed out that irrigation frequency is one of the most important issues that determine the increase of productivity and soil quality in agriculture. In this study, water stress in pepper plants was tried to be detected by using spectral images, and classification of feature vectors related to the data was performed with K-NN and Artificial Neural Networks methods [7]. Gunes et al. used the VGG16 model, a deep learning technique, for the classification of hazelnut products. In this study, a large dataset consisting of hazelnut images was created. In addition, this dataset was used in different ratios to detect and classify the ratio of hazelnut kernel, damaged hazelnut, and quality hazelnut, and the performance of the model was determined [8]. Boyar et al. proposed the Yolo-v5 model, a machine learning algorithm, to detect healthy and diseased regions in hazelnut tree leaves. In this study, a unique data set was processed, and an object detection model, the Yolo model, was used to detect powdery mildew disease on the leaf image. According to the performance results of the model, a successful detection mechanism was developed, and a scientific contribution was made to increase hazelnut production efficiency [9]. Ngugi et al. conducted a comprehensive literature search and review of the most recent studies in the detection and classification of plant diseases. In this study, performance analysis was performed using state-of-the-art machine learning (ML) and deep learning (DL) models. They stated that traditional ML and convolutional neural network (CNN) models are often preferred in many studies. They suggested that new DL algorithms such as capsule neural networks and image transformers should be focused on. They also emphasized that the datasets used are only for specific crops and a large image dataset with a wider range of crops is needed. Instead of focusing on ML or DL models in plant disease detection, they suggested the development of a combination of ML and DL algorithms for the detection of several plant diseases [10]. Khalid et al. emphasized that traditional detection methods for early and accurate diagnosis of plant diseases are inefficient, laborious, and prone to false results. In their study, they investigated the effective segmentation ability of DL models by focusing on CNN and MobileNet architectures. In addition, they included eXplainable Artificial Intelligence (XAI), which enables the explanation of disease markers in plant images with the GradCAM technique in the decision-making process of these models. According to the performance results, it was revealed that the DL model was more successful in image segmentation in plant disease detection [11].

Artificial intelligence technology, which has become pervasive in almost every area, is increasingly used in agriculture for determining planting areas, classifying planted products, and deriving statistical results from these areas. Studies conducted for determining and classifying planting areas in agricultural lands gain importance in preventing illegal, prohibited, and incorrect cultivation of products. In particular, in order to prevent the abuse of the misuses of government subsidies provided to the producers for agricultural support and to make these expenditures in the right areas, their detection can be done quickly thanks to the use of machine learning methods with aerial images. In this context, a crop classification study conducted with data obtained from UAV and satellite radar images provides great savings in terms of time, cost a high-technological environment. In addition, in studies carried out with deep learning models in order to increase production, grow quality products, and increase precision in agriculture, crop variety and disease classification can also be done with machine learning models.

In this paper, we utilize an existing dataset, created and labeled from aerial images of corn and wheat crops, to compare the performances of machine learning methods commonly used in the literature for the classification of cultivated land. The primary aim of the study is to develop a method for identifying the appropriate machine learning algorithm works better to classify corn and wheat plant species from multispectral aerial images that can be collected by UAV or satellite radar systems over cultivated lands in the GAP region. The reference dataset consists of radar optical image features of corn and wheat plants. Due to the complexity and large size of this dataset, model performance is low, training time is lengthy, and achieving high accuracy is very difficult. However, by mixing the dataset, we can reduce the possibility of memorization and increase the accuracy rate. This process necessitates a significant amount of time and robust computer hardware. In addition, model performance decreases and training time increases as the number of classes and features increases. Although this is a very common problem when applying machine learning techniques, class imbalance correction techniques such as dataset reduction and feature selection can be used to counteract this bias [12]. After the dataset imbalances are removed, the models are trained using machine learning algorithms. Since there are many machine learning models in the literature and it would be time-consuming to evaluate all of them, this study compares the effectiveness of the 4 most widely used machine learning algorithms (DT, K-NN, NB, and SVM) for plant species classification. The studies concluded that data obtained from optical radars can successfully classify the croplands cultivated with corn and wheat on agricultural lands in the GAP region. This study will be a quality reference for statistical information and plant classification for the GAP region.

2. MATERIAL AND METHOD

2.1. Dataset

The dataset used is two-time optical radar data with combined temporal, spectral, textural, and polarimetric features for cropland classification provided by UC Irvine Donald Bren School of Information & Computer Sciences [13]. The imagery was collected by RapidEye satellites (optical) and Unmanned Aerial Vehicle Synthetic Aperture Radar (UAVSAR) on July 5 and 14, 2012, over an agricultural region near Winnipeg, Manitoba, Canada. Only data pertaining to corn and wheat species were retained, while data related to other plant species were removed from the dataset. In addition, the wheat class has been relabeled as ‘2’. It consists of two classes (1-Corn, 2-Wheat), 2x49 radar, and 2x38 optical, totaling 174 features and 124236 rows of data.

In this dataset, two crop type classes, namely Corn and Wheat, were studied for the classification of cultivated lands in the agricultural areas of the Southeastern Anatolia Project (GAP) region. It is anticipated that if high performance is achieved with the machine learning models used with this dataset, this study will serve as a quality reference for the GAP region.

In all models, the first 80% of the dataset was allocated for training, and the remaining 20% for testing. The network was trained with and without normalizing the dataset, and the highest accuracy and performance results were obtained when the network was trained without normalizing the dataset. In addition, all models were trained and compared separately when the dataset was randomized and when it was not. In this case, the randomized dataset provided the best results, and the study continued with it.

2.2. Machine Learning Methods

DT, K-NN, NB, and SVM models, which are the most favored in classification tasks within supervised learning frameworks of machine learning, were used. The flow diagram depicting the stages of dataset organization, including its division for training, and testing, as well as the execution of machine learning models, is shown in Figure 1.

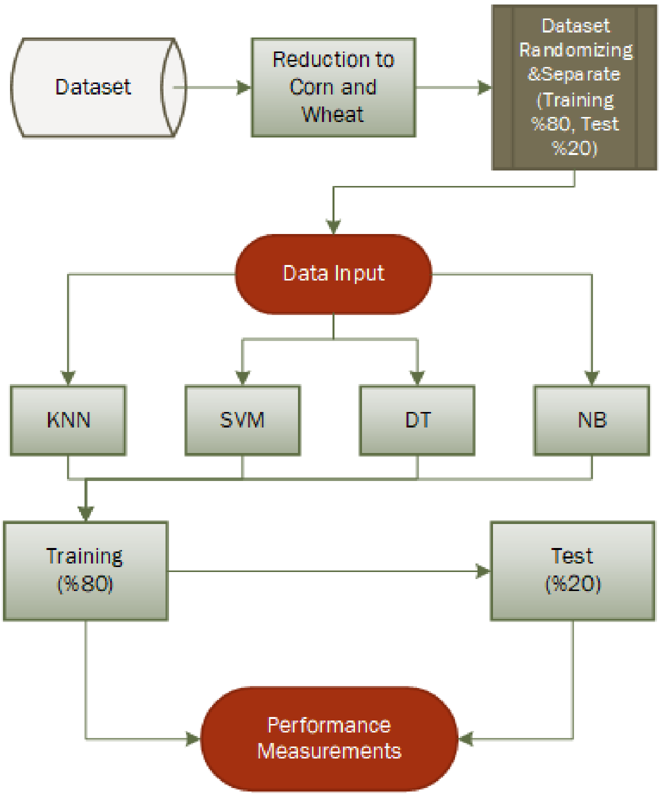

Figure 1. Flow chart

2.2.1. Decision Tree

The DT model can be utilized for both classification and regression purposes. DT is represented by a tree structure that makes decisions based on features in the dataset and is used to model complex relationships in the data using the features and target variables in the dataset [14-16]. Here, the target variables can be labels for classification or target variable values for regression. The two internal nodes that form the branches are the decision-making dataset (decision node), which consists of various branches in the algorithm, and the finalizing leaf node, which is the output of the decision nodes and has no other branches. Its shape resembles a tree. In general, decision trees start from a root node and continue with a series of internal nodes and leaf nodes. Each internal node performs a test from a feature or attribute and selects a branch as a result of this test [17]. Leaf nodes contain the results [14]. DT basically divides the tree into subtrees based on the answer to the question, i.e., whether it is true or false [17].

When constructing a DT, determining which feature to test at each internal node is crucial. Feature selection can be done using measures such as information gain, entropy (amount of homogeneity) or other metrics based on the features and target variable of the dataset [15].

Entropy, a dataset's homogeneity or uncertainty, is a measure of information. Here, $\boldsymbol{S}$ represents the dataset, $\boldsymbol{c}$ represents the number of classes, and $\boldsymbol{p_i}$ represents the probability of each class. The following formula facilitates entropy calculation:

$$E(S) = -\sum_{i=1}^{c} p_i \log_2(p_i) \tag{1}$$

Information gain, measures how much the entropy of the dataset decreases when a feature is used. Here, $\boldsymbol{S}$ represents the original dataset, $\boldsymbol{A}$ represents the selected feature, $\boldsymbol{Values(A)}$ represents the values that the feature $\boldsymbol{A}$ can take, $\boldsymbol{S_\vartheta}$ represents the examples with the value $\boldsymbol{v}$ for the feature, and $\boldsymbol{|S|}$ represents the size of dataset. The following formula calculates the information gain:

$$IG(S,A) = E(S) - \sum_{\vartheta \in Values(A)} \frac{|S_\vartheta|}{|S|} \times E(S_\vartheta) \tag{2}$$

DT is easy to understand, highly interpretable, and quite resilient to imbalanced and missing data in the dataset. However, they may exhibit a tendency to overfit, so proper parameter tuning and model validation are important [15].

2.2.2. K-Nearest Neighbors

The K-NN algorithm is a fundamental and efficient method for data classification, especially favored in scenarios with high uncertainty. It was created for uniform analysis when decision-making based on probabilistic densities via parametric estimate proves difficult. Calculations indicate that when k=1 and n approaches infinity, the classification error of K-NN is constrained to double the error rate of Bayes [17]. K-NN is a straightforward and efficient machine learning technique, predominantly utilized for classification and regression applications, with a bias towards classification issues. As indicated by its designation, it forecasts outcomes based on the predominant influence of neighboring data points [18].

2.2.3. Naive Bayes

The NB model is a parametric supervised classifier grounded in the Bayesian probability theorem and the principle of strong independence among features [20, 21]. This classifier is referred to as 'naive' due to its assumption that each characteristic is independent of the others in the classification process. The likelihood of a feature being associated with a specific class is determined by training the model using a training dataset. The program employs this data to compute the mean vectors and covariance matrices for each class to facilitate predictions [19, 22]. The Bayesian theorem calculates the probability of an event, while the Naive Bayes classifier identifies the class of a data point using the subsequent formula:

$$P(c_k|x) = \frac{P(x|c_k) \times P(c_k)}{P(x)} \tag{3}$$

$\boldsymbol{P(c_k|x)}$, is the probability that a data point belongs to class $\boldsymbol{c_k}$ given the occurrence of $\boldsymbol{x}$. $\boldsymbol{P(c_k)}$, is the prior probability of the class (the probability of $\boldsymbol{c_k}$). $\boldsymbol{P(x|c_k)}$, is the probability that a data point belongs to class $\boldsymbol{x}$ given that $\boldsymbol{c_k}$ has occurred. $\boldsymbol{P(x)}$, is the prior probability of the predictor (the probability of $\boldsymbol{x}$).

2.2.4. Support Vector Machines

The SVM model used in classification problems is a machine learning technique based on the concept of an optimal separating hyperplane, which usually discriminates between two classes [23]. Basically, SVM draws a decision boundary between classes and classifies data points according to which side of this boundary they fall on. This decision boundary is set in such a way that the data points achieve the maximum margin. SVM uses a set of kernel functions, such as linear, polynomial, and radial basis functions, which can transform the low-dimensional input space into a higher-dimensional space [24]. The SVM model is used in many fields such as driverless cars, chatbots, face recognition, etc. [17]. SVM can be a two-class or a multi-class model (a combination of a chain of two-class SVMs) [23]. To train the algorithm, SVM learns the boundary between training samples belonging to different classes, projects them into a multidimensional space, and finds a hyperplane or a set of hyperplanes that maximizes the discrimination of the training dataset between a predefined number of classes [21, 25, 26]. The SVM distinguishes two classes and finds the optimal hyperplane using the following equation [23]:

$$\min_{w,b,\varepsilon} : \frac{1}{2} w^T w + c \sum_{i=1}^{1} \varepsilon_i \tag{4}$$

This formula is valid under the following constraints:

$$y_i(w^T \varphi(x_i) + b) \geq 1 - \varepsilon_i \qquad \varepsilon_i \geq 0 \tag{5}$$

Here, $\boldsymbol{w}$ denotes the normal vector to the hyperplane, $\boldsymbol{b}$ (bias) represents the distance of the hyperplane from the origin, $\boldsymbol{\varepsilon_i}$ are positive slack variables, and $\boldsymbol{c}$ (> 0) is the penalty parameter for errors [23].

SVM minimizes the misclassified examples on the decision boundary. However, sometimes datasets are not linearly separable. In such cases, the $\boldsymbol{c}$ parameter can be used to adjust the misclassification errors of the decision boundary. $\boldsymbol{c}$ is a hyperparameter that needs to be tuned during training. Larger values of $\boldsymbol{c}$ impose a higher penalty on misclassification errors, while smaller values of $\boldsymbol{c}$ impose a lower penalty on misclassification errors [23].

In machine learning methods and statistical modeling, several mathematical calculation methods are used to assess categorization performance and evaluate the efficacy of test findings and the methodologies utilized. AUC, F1-Score, specificity, precision, recall, and accuracy are the most common metrics used in classification problems and statistical calculations. Each metric evaluates different aspects of the model and is useful for specific situations. In this study, calculations are made using these metrics in accordance to accurately assess the performance results.

2.3. Performance Metrics

In machine learning methods and statistical modeling, several mathematical calculation methods are used to assess categorization performance and evaluate the efficacy of test findings and the methodologies utilized. AUC, F1-Score, specificity, precision, recall, and accuracy are the most common metrics used in classification problems and statistical calculations. Each metric evaluates different aspects of the model and is useful for specific situations. In this study, calculations are made using these metrics in accordance to accurately assess the performance results.

The complexity matrix is a 2x2 matrix that visually illustrates the efficacy of the used classification model. It is widely used particularly for two-class classification problems, but can also be generalized to multi-class problems. Figure 2 illustrates the correlation between actual classes and predicted classes as represented in this matrix.

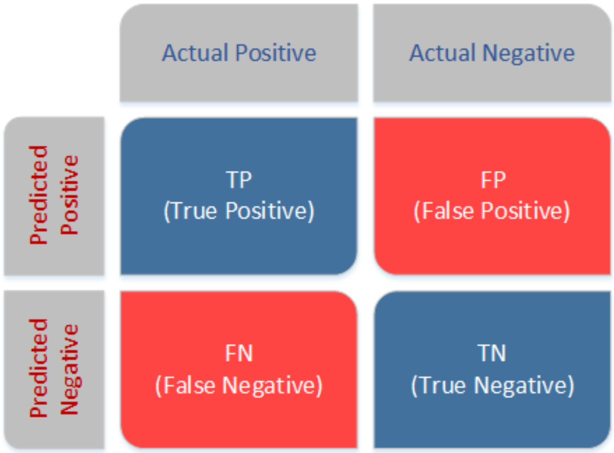

Figure 2. Confusion matrix

True Positive (TP) are accurate instances that the model identifies as positive. **True Negative (TN)** are accurate instances that the model categorizes as negative. **False Positive (FP)** are negative instances that the model by mistake categorizes as positive. **False Negative (FN)** are positive instances that the model by mistake categorizes as negative (missed) [6, 19, 27, 28].

Accuracy, quantifies the proportion of true predictions made by the model. It is the proportion of accurately classified instances to the total number of instances. However, it can be misleading in imbalanced datasets because errors in the minority class may be masked by the accuracy of the majority class [6, 19, 27, 28].

$$Accuracy = \frac{TN+TP}{TN+TP+FN+FP} \tag{6}$$

Precision, quantifies the ratio of true positive predictions to the total positive predictions made. It is particularly important in situations where reducing false positives is crucial, such as ensuring that a non-diseased individual is not incorrectly diagnosed. For instance, when diagnosing a disease in a plant species, the precision calculation is crucial to avoid misdiagnosing the non-diseased plant [6, 19, 27, 28].

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

Recall (Sensitivity), quantifies the ratio of true positive cases accurately detected by the model. It is *important* for situations where false negatives are to be reduced. For instance, it is crucial not to miss a diseased plant [6, 19, 27, 28].

$$Recall = \frac{TP}{TP+FN} \tag{8}$$

Specificity, quantifies the ratio of true negative instances accurately identified as negative. Important for situations where the false positive rate is to be reduced [6, 19, 27, 28].

$$Specificity = \frac{TN}{TN+FP} \tag{9}$$

The **F1-score** is the harmonic mean of precision and recall. It is beneficial in situations requiring a balance between precision and recall, particularly in imbalanced datasets or when balancing precision with recall is desired. The F1-Score is utilized when the model needs to both effectively predict positive classes (recall) and avoid false positives (precision). When calculating the model's performance, an F1-Score closest to 1 (one) is expected [6, 19, 27, 28].

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{10}$$

The AUC quantifies the area beneath the ROC (Receiver Operating Characteristic) curve and serves as a tool for evaluating the efficacy of a classification model. The ROC curve is a graphical representation used to evaluate the performance of a classification model. This metric summarizes the performance of a classification model at all threshold values with a single numerical value. The AUC value typically ranges from 0 (zero) to 1 (one), where a higher AUC value indicates better model performance. The AUC value can be calculated using the formulas for sensitivity and specificity as follows [23].

$$AUC = \sum_{i=1}^{n-1} \frac{1}{2} (Recall_i + Recall_{i+1}) \times (Specificity_{i+1} - Specificity_i) \tag{11}$$

3. RESULTS AND DISCUSSION

We built the models on a workstation computer with an Intel Xeon E-2221G CPU, 16GB of RAM, and an NVIDIA Quadro P620 graphics card. We allocated 80% of the dataset for training, and 20% for testing in all models. The training and testing performance results of the models are as shown in Tables 1, and 2, respectively.

Table 1. Training performance results of the models

	Accuracy	Specificity	Precision	Recall	F1-Score	AUC
DT	0.9998	0.9999	0.9998	0.9996	0.9997	0.9997
KNN	0.9997	0.9998	0.9997	0.9993	0.9995	0.9996
NB	0.9932	0.9929	0.9848	0.9938	0.9893	0.9934
SVM	0.9999	0.9998	0.9999	0.9998	0.9999	0.9999

Table 2. Test performance results of the models

	Accuracy	Specificity	Precision	Recall	F1-Score	AUC
DT	0.9983	0.9992	0.9983	0.9962	0.9973	0.9975
KNN	0.9996	0.9999	0.9997	0.9992	0.9994	0.9996
NB	0.9895	0.9926	0.9840	0.9830	0.9835	0.9862
SVM	0.9998	0.9999	0.9996	0.9994	0.9996	0.9996

Figures 3, 4, 5, and 6 illustrate the graphical comparison of the training and test performance outcomes of the models.

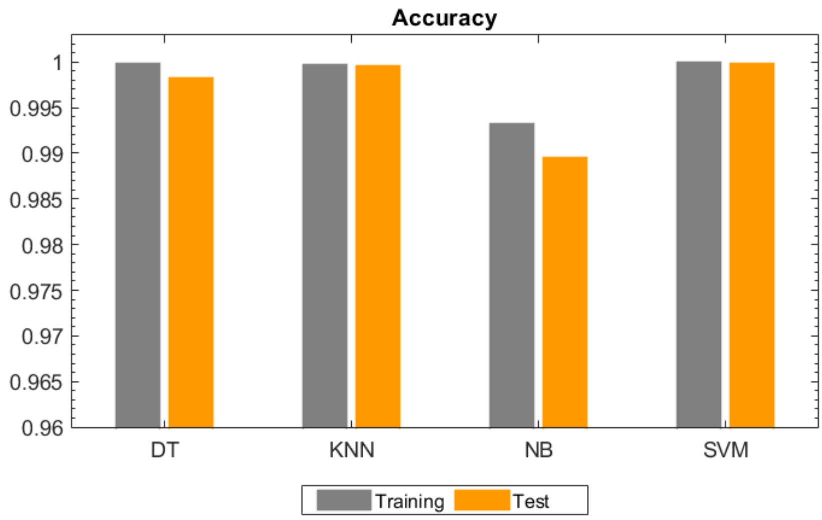

Figure 3. Accuracy performance graph of the models according to training and test data

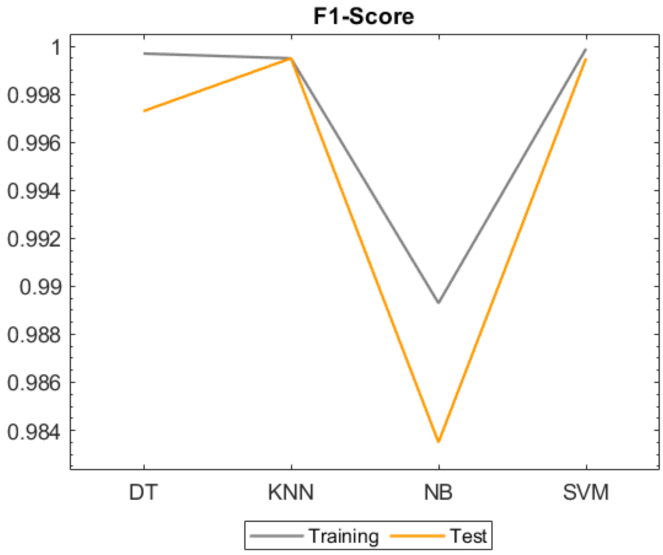

Figure 4. F1-Score performance graph of the models according to training and test data

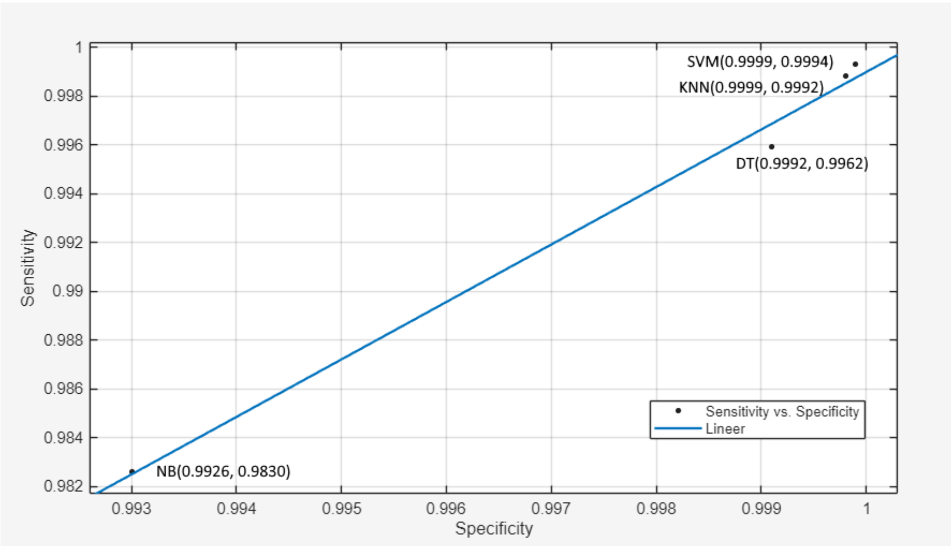

Figure 5. Specificity and sensitivity performance graph of the models according to test data

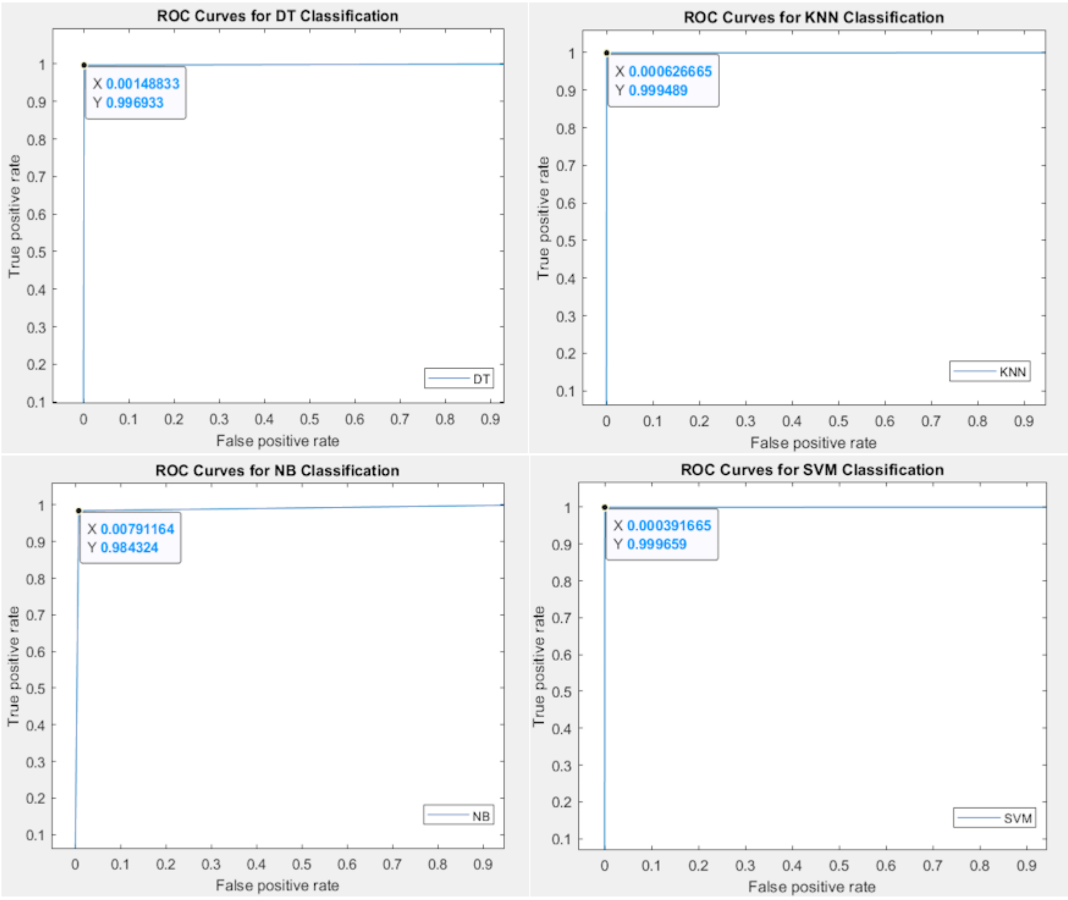

Figure 6. ROC curves graphs of the models according to test data

In addition to these results, the results obtained in this study were compared with the studies conducted. The results obtained in the study were compared with the studies presented in [29] and [30]. The comparison results are given in Table 3.

Table 3. Comparison Results

	Li et al. [29]	Sankaran et al. [30]	This Research
Accuracy	0.9862	0,9930	0.9998

When the results given in Table 3 are considered, it is understood that the results of the method proposed in the study are acceptable.

4. CONCLUSION

In this paper, we compared machine learning models that can be used for the identification and classification of corn and wheat cultivated agricultural lands in the GAP region by using an aerially captured and combined optical radar dataset from agricultural lands in the Canadian region as a reference and determined the most suitable methods based on performance results. We used supervised learning models such as DT, K-NN, NB, and SVM among the machine learning methods and compared their performances. The dataset contains a total of 174 polarimetric and optical features and 124236 rows of data for two plant species (corn, wheat). We used the dataset in two distinct ways; the first version of the dataset ordered the features as corn and wheat, leading to lower performance and accuracy rates, while the second version randomly processed the data, resulting in higher performance and accuracy rates. In all the models we analyzed, we evaluated the Area Under the Curve, F1-Score, and accuracy measures. According to the accuracy criterion results, SVM = 0.9998 > K-NN = 0.9996 > DT = 0.9983 > NB = 0.9895. According to the F1-Score results, SVM = 0.9996 > K-NN = 0.9994 > DT = 0.9973 > NB = 0.9835. These comparisons are based on the results of the model in the test phase. This study has demonstrated that classification applications for agricultural products can yield high accuracy results in this constantly developing field. In the light of the results obtained in Table 3, it is concluded that especially the wheat and corn species classified in this study can be distinguished effectively with the relevant data collection tool. In future studies, a large data set consisting of more plant species can be trained to increase the variety of crops that can be detected. By providing an infrastructure that includes the pre-trained model, a web or desktop application designed for the end user with an intuitive user interface can be developed. Such an application can expedite the government's crop detection process and timely intervene against corruption. It can also allow farmers to statistically determine the type and quantity of crops they plant.

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DECLARATION OF COMPETING INTEREST

The authors declared that no ethics committee permission was required for the materials and methods used in this article.

CONFLICT OF INTEREST

No conflict of interest has been declared in this study.

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Research Article

The Effect of Laparoscopic Devices on Cholecystectomy Surgeries

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ABSTRACT: Laparoscopic devices have had significant effects in many areas of surgery, and have also greatly affected gallbladder surgeries. Aim and method: For these reasons, to investigate the effect of laparoscopic devices on bile duct injuries and surgical treatment; articles published on this subject were analyzed and evaluated in our study. As a result of our study, it was shown that providing safe surgical conditions, making the bile ducts visible before surgery, and performing these surgeries by experts in hepatobiliary surgery can significantly reduce BDI rates with laparoscopic devices. In addition, early surgical intervention, Roux en-Y hepatobiliary anastomosis technique in major injuries, and laparoscopic and robotic surgery can provide more successful results with 3D imaging in bile duct injuries. Conclusion: According to the results of our study; laparoscopic devices have led to exciting developments in cholecystectomy surgeries. Since the abdominal wall is not opened, surgery times have been significantly shortened and excellent cosmetic results have been obtained. On the other hand, since 3D vision cannot be provided with this method, there has been an increase in the incidence of serious complications such as bile duct injuries. Therefore, it would be more appropriate to use safe surgical methods in laparoscopic cholecystectomies.

KEYWORDS: Laparoscopic devices, cholecystectomy, bile ducts, injury.

ÖZET: Laparoskopik cihazlar cerrahide birçok alanda önemli etkiler yarattığı gibi, safra kesesi ameliyatlarınıda büyük ölçüde etkilemiştir. Amaç ve Yöntem: Bu nedenlerle çalışmamızda laparoskopik cihazların safra yolu yaralanmaları ve cerrahi tedavisi üzerindeki etkilerini araştırmak amacıyla bu konuda yayınlanmış makaleler analiz edilmiş ve değerlendirilmiştir. Çalışmamızın sonucunda güvenli cerrahi koşulların sağlanması, safra yollarının ameliyattan önce görünür hale getirilmesi ve bu ameliyatların hepatobiliyer cerrahi konusunda uzman kişiler tarafından yapılmasının laparoskopik cihazlarla BDI oranlarını önemli ölçüde azaltabileceği gösterilmiştir. Ayrıca erken cerrahi müdahale, majör yaralanmalarda Roux en-Y hepatobiliyer anastomoz tekniği ve laparoskopik ve robotik cerrahi safra yolu yaralanmalarında 3 boyutlu görüntüleme ile daha başarılı sonuçlar elde edilebildiği ortaya konulmuştur. Değerlendirme: Yaptığımız çalışmanın sonuçlarına göre; laparoskopik cihazlar kolesistektomi ameliyatlarında heyecan verici gelişmelere yol açmıştır. Karın duvarı açılmadığı için ameliyat süreleri önemli ölçüde kısalmış ve mükemmel kozmetik sonuçlar elde edilmiştir. Öte yandan bu yöntemle 3 boyutlu görüş sağlanamadığı için safra yolu yaralanmaları gibi ciddi komplikasyonların görülme sıklığında artış olmaktadır. Bu nedenle laparoskopik safra kesesi ameliyatlarında güvenli cerrahi yöntemlerin kullanılması daha doğru olacaktır.

ANAHTAR KELİMELER: Laparoskopik cihazlar, kolesistektomi, safra yolları, yaralanma.

1. INTRODUCTION

Professor Muko of Boblingen performed Laparoscopic Cholecystectomy (LC) for the first time on a patient in Germany in 1985 and opened a new era in hepatobiliary surgery [1]. Thus, cholecystectomy surgeries began to be performed much more quickly than open surgery, without opening the abdominal wall, and with excellent cosmetic results. After this fantastic new surgical method by Boblingen, LC was predominantly applied in cholecystectomy surgeries and complications of different nature and rates began to occur compared to open cholecystectomy (OC).

In today's world, approximately 500,000 LC surgeries are performed each year. As a result, complications such as bile duct injuries (BDI), vascular injuries [2,3,4], stone formation in the cystic duct stump, intestinal injuries [3], lymphatic injuries [5], and bilioma formation [6] may occur, which can sometimes result in death. Despite this, the prevalence of laparoscopic methods in cholecystectomies has significantly decreased the incidence of some complications such as postoperative hernia and wound infection [3]. Since BDI is still the most common complication in LC operations, the effects of LC on BDI and surgical treatment were reviewed in our study.

2. EFFECTS OF LAPAROSCOPIC CHOLECYSTECTOM ON BILE DUCT INJURIES

The most important technical difference in LC operations compared to OC is that the vision during the operation is 2-dimensional rather than 3-dimensional, and there is no depth vision. Therefore, the risk of trauma is higher in all kinds of manipulations performed in the abdomen. Although morbidity and mortality rates can be significantly reduced with LC compared to OC, a significant decrease in BDI rates has not been achieved despite the many years that have passed (Table 1) [3,7,8,9,10, 11,12]. This may be due to the lack of 3-D vision in LC surgeries. BDI incidences according to the results of studies by some authors, in LC and OC operations are shown in (Table 1).

Table 1. BDI incidences according to the results of studies by some authors, in LC and OC operations.

Author	Ref. No	Number of cases	OC*	LC*	BDI*** Incidence
Deziel	3	77.604		+	0.6
Reinso	7	29.739		+	0.81
Tantia	17	13.305		+	0.39
Elser	10	769.792		+	0.1
Gutierrez	11	387.501		+	0.2
Barret	24	319.184		+	0.23
Tangarona	37	1.630		+	0.95
Tangarona	37	3.054	+		0.6
Roslyn	15	42.474	+		0.02

OC* : Open cholecystectomy
LC** : Laparoscopic cholecystectomy
BDI***: Bile duct injury

Emara et al. reported in a study that BDIs are seen at a higher rate in LCs than in OCs [13]. In a study conducted by Deziel in 1993 in US, the BDI incidence was found to be 0.6% in 77,604 LC cases [3]. In a study conducted by Reinso et al. on 29,739 LC cases, the overall BDI incidence was found to be 0.81%, minor injuries 0.68%, and major injuries 0.13%(Table 1) [7]. In a study conducted by Kaman et al., it was reported that the mechanism and extent of major BDIs in LC and OC were different, but the clinical findings and BDI level were the same [14]. In a study conducted by Roslyn et al. on 42,474 cases who underwent OC, the incidence of BDI was 0.02% and overall mortality was 0.17% [15]. The authors reported that the mortality rate was related to the duration of hospitalization, age of the patients, admission status (elective, urgency emergent) and the status of the disease. In a study conducted by Doğan et al., it was reported that morbidity and mortality rates were high in BDI cases that underwent reconstruction, and also quality of life decreased for many years after treatment [16]. A study conducted by Tantia et al. analyzed 13,305 LC cases performed by a single center and single surgeon team. BDI was detected in 52 (0.39%) cases. Intraoperative diagnosis was made in 32% (0.24) of these cases and postoperative diagnosis was made in 20 cases. There was no mortality. The authors reported that LC is as safe a method as OC when performed in accordance with safe surgical standards (Table 1) [17]. In a study conducted by Zanghami et al. in Iran, the most commen symptoms of BDIs are fever, jaundice, pain, and pruritus were reported. It has been stated that the most important laboratory findings are increased bilirubin level, leukocytosis and increased liver function tests [18].

In a multicenter analytical study by Moldovan et al. revealed 108 BDI and vascular injury in 16,559 LC cases. A clinical and surgical algorithm was generated for management in iatrogenic BDI cases (Table 1) [2]. In a study conducted by Deziel and colleagues published in the same year, 1.2% of 77,604 cases undergoing LC were converted to OC, and BDI was seen in 0.6% of cases [3]. Elser and colleagues stated the BDI rate as 0.1% in a large LC series of 769,792 cases [10]. According to the results obtained in the same study, it was reported that mortality increased in cases with biliary colic, obesity, pancreatic and chronic liver disease, and choledochal injuries, and costs decreased in operations performed on the same day. They stated that USG and contrast-enhanced MRI are safe and effective in diagnosis and endoscopic management in BDIs. In a study by Gutierrez et al., it was reported that BDI was seen in 0.2% of 387,501 LC cases [11]. The authors determined that acute cholecystitis, obesity and steatohepatitis constitute the lethal triad in LCs. They reported that the BDI rate increased to 1.49% in cases with lethal triad and was 0.09% in other cases and lethal triad is an independent risk factor according to the results of multivariate analysis. In a study conducted by Indal and colleagues, it was reported that LC operations should be performed by hepatobiliary specialists, and that BDI rates can be reduced when safe LC is performed using methods such as B SAFE strategy, R4U line, Bail-out [19]. Seshadri and colleagues reported in a study that the most important risk factors leading to BDIs are anatomical variations of the bile ducts, and therefore, in difficult cholecystectomies, a subtotal or top-down cholecystectomy technique should be performed to avoid the risky hepatocystic triangle [20].

Acute cholecystitis is one of the most important risk factors for the occurrence of BDI in LC operations. For this reason, many authors have reported that acute cholecystitis cases should be classified as difficult cholecystectomy and safe cholecystectomy methods should be performed during the operation [11, 20, 21, 22,23]. In a study conducted by Ali et al., it was reported that 70% of 37 BDI cases underwent LC and 29.7% underwent OC, and one case with bile leakage and bilioma formation was treated with endoscopic percutaneous intervention [6]. Some studies have reported lower BDI incidence in LC operations.

In a study conducted in the USA by Barnett et al., it was reported that BDI was seen in 741 cases (0.23%) in a LC series of 319,184 cases [24]. Some authors explain the low BDI rates by the fact that LC is a more minimally invasive procedure [25]. In a study conducted by Lopez et al., they aimed to define a Textbook Outcomes (TO) to determine the ideal treatment of BDIs and collected data from 27 patients between 1990 and 2022. TO results were obtained in 394 of the 508 patients included in the study. Complication rates were determined as 11.9% in the TO group and 8% in the non-TO group. Based on these results, they reported that TO largely depends on where the BDI is treated and the type of wound [26]. In a study conducted by Symeonidis et al., they formed a new classification (BILE Classification) and algorithm for better management of iatrogenic BDIs. They reported that this practical classification and treatment algorithm was more effective in BDI management [8]. In a study conducted by Cai et al., in which fluorescence cholangiography was used to prevent BDIs in LCs, patients were divided into two groups; indocyanine was given intraglandularly to the the first group (Group A) and intravenously to the second group (Group B). At the end of the study, it was reported that the operative time was shorter in the group A and preoperative diagnosis was made more easily [27]. It was also determined that no fluorescence was observed in the group B, if there was an impacted stone. In a study conducted by Symeonidis et al., a randomized controlled standard cholangiography and indocyanine green fluorescence cholangiography were compared for biliary anastomosis visualization and the results were reported to be the same [28]. In a study conducted by Edebo et al., they compared the effects of intraoperative laparoscopic USG and intraoperative cholangiography to increase biliary tract visualization in LC. According to the findings obtained at the end of the study, no significant difference was found between the two methods in of mortality, BDI incidence, and retarded gallstone. However, the rate of conversion to OC was found to be lower in cases with laparoscopic USG, probably due to the shorter imaging period [29]. In a study conducted by Freesmeyer et al., it was reported that (68Ga) Ga-TES-DAZA and PET-CT were effective methods for localization of biliary leakage when BDI occurred in cases undergoing LC [30].

Critical View of Safety (CVS) can significantly reduce BDI rates in LC cases. In a study conducted by ACB Blitzikov, it was shown that the application of the method described by Strasberglin was effective in preventing significant complications in LCs [31]. According to some authors' studies, BDI rates in cases with and without CVS are shown in (Table 2).

Table 2. BDI rates in cases with and without CVS in some authors' studies.

Author	Ref. No	CVS* LC**	NON- CVS LC	BDI*** rate %
Klos	35	+		0.06
Bansal	33	+		0.05
Singh	32	+		0
Singh	32		+	2
Deziel	3		+	0.6

CVS* : Critical view of safety.
LC** : Laparoscopic cholecystectomy
BDI*** : Bile duct injury

In a study conducted by Singh et al., the effect of CVS on preventing BDI in LCs was investigated. As a result of the study, CVS was achieved in 14 out of 100 LC cases. It was reported that in all of these cases, the hospitalization period was long, 12 of them were converted to OC, and BDI occurred in 2% of the cases (Table 2) [32]. In a study conducted by Bansal et al., CVS was performed under proctored preceptorship in 3726 LC cases. It was shown that major BDI could be reduced to rates as low as 0.05% with this method(Table 2)[33].In a prospective study conducted by Ortenzi et al., patient groups who underwent intraoperative cholangiography using white light for CVS were compared, and it was determined that the most effective method for CVS was near-infrared fluorescence cholangiography[34].In a study conducted by Klos et al., it was shown that BDI occurred in 186 out of 76,345 cholecystectomies in the Czech population (0.24%). LC was performed in 0.84.7% of these cases and OC in 15.3%. BDI occurred in 0.06% of LC cases that underwent CVS and in 1.28% of OC cases. According to the results of the study conducted by the authors, it was reported that BDI rates were very low in LCs performed in accordance with CVS standards (Table 2) [35]. In a study conducted by Manal et al., it was reported that the average age of 60 BDI cases seen after LC was 45 years and 75% of the cases were female [36]. It was stated that the most important symptoms in these cases were jaundice, abdominal pain and bile discharge and the most appropriate methods for imaging were magnetic resonance cholangiopancreatography. It was reported that the most frequently performed operations were Roux en-Y choledochojeumostomy, choledochoduodenostomy, and primary suture with T tube. Bile leakage (10%), wound infection (15%) and recurrent cholangitis (5%) occurred as complications.

In a prospective study conducted by Tangarona et al., patients were divided into 2 groups; LC surgeries were performed in one group and OC surgeries were performed in the other group. According to the results of the study, BDI rates were higher in the LC group [37].

3. EFFECTS OF LAPAROSCOPIC SURGERY ON SURGICAL TREATMENT OF BILE DUCT INJURIES

Laparoscopic and robotic surgery have also had significant effects on the surgical treatment of BDI cases. In a study conducted by Cai et al., it was stated that the place of endoscopic management in BDIs is increasing. It has been reported that applications such as endoscopic duodenal papillary sphincteromy, endoscopic hepatobiliary drainage, and endoscopic biliary stent implantation have a significant effect on the surgical treatment of BDIs occurring in LCs [23]. In a study conducted by Yang et al., early surgical repair (average 14.2 days) was performed with 3D visualization technique in 15 cases with BDI. Roux-en-Y anastomosis and hepaticojejunostomy were performed in all cases. The average operation time was 156.4 minutes, and the average hospitalization time was 16 days. Mild bile leakage was observed in one case, which healed with conservative treatment. The patients were followed up for an average of 34 months and no complications such as stone formation or anastomotic stenosis were observed [38]. This study demonstrated the importance of 3D vision in surgical treatment when BDI occurs in LCs. In a study conducted by Petkov et al., in the last 10 years, minimally invasive interventions were performed with endoscopy and interventional radiology in 30 cases with BDI, and the cases were treated with zero mortality. Therefore, the importance of multidisciplinary intervention in BDI cases was emphasized [25].

In a study conducted by Cubisina et al., it was reported that safe and effective repair can be performed with minimally invasive robotic surgery in BDI injuries occurring in LCs [39]. In a study conducted by Raysan et al., bile ducts reconstruction was performed with robotic surgery in 33 patients with BD injuries [40]. The average operation time was 272 minutes and the average hospital stay was 4 days. The patients were followed up for an average of 33 days. Only one case underwent revision due to stricture. No other complications were observed in any of the patients. Mortality was zero. According to the results of the study, it was reported that robotic surgery reconstruction is an effective and safe method when BDI occurs in LCs.
Some articles reporting that choledochal injuries are more common in robotic cholecystectomies than in OC. In a retrospective study by Dicken et al., it was reported that common bile duct injuries were significantly more common in robotic cholecystectomies than in LCs [41].

In a study conducted by Montalvo-Save et al., the main bile ducts were replaced with bioprostheses in 16 male pigs. During the 24-month follow-up period, liver function tests and epithelialization were found to be normal, and bile flow continued normally. The authors reported that reconstruction with bioprosthesis in BDIs may be safe and effective [42].

In a study conducted by Chance et al., tips were given and tricks were emphasized to prevent BDI in LCs [43]. It was stated that obesity, liver cirrhosis, duration and severity of cholecystitis, anatomical variation, surgeon experience and comorbidity were the most important risk factors. It was reported that Rouvieners Sulcus, segment 4, umbilical fissure line were important anatomical markers for safe dissection in order to reduce BDI rates. It was emphasized that dissection in the hepatocystic triangle was risky and that the surgeon should convert to subtotal cholecystectomy or OC when necessary. According to the results of their study, there was a shorter hospitalization time in cases with robotic biliary anastomosis (36.1%) compared to those with laparoscopic anastomosis (63.1%) and no case was converted to OC, while OC was converted to 4 of the cases with laparoscopic anastomosis. It was observed that morbidity was similar in both groups. In a study conducted by Blohm et al. on 154,937 cholecystectomy cases, it was revealed that BDI rates were affected by the number of surgeries performed by the surgeon. The incidence of BDI was found to be higher in low-volume surgeons [44].In a study conducted by Tinoco et al., it was reported that laparoscopic hepaticojejunostomy is an effective treatment method with low complication rates in cases with total circumferential BDI injury[45]. It was emphasized that LC was performed in 83.3% of the cases with BDI and OC was performed in 13.6%, therefore, it is necessary to comply with safe surgery standards in LC cases.

In a study conducted by Khalit et al., an artificial intelligence algorithm was developed to prevent BDIs with real-time intraoperative decision support in LCs and to warn to stop in dangerous areas and continue dissection in safe areas. According to the results obtained in the study, it was shown that intraoperative decision support with artificial intelligence was effective in preventing BDIs [46].

4. CONCLUSION

According to the results obtained in our study, in cholecystectomy surgeries performed with laparoscopic devices, BDI rates are higher than OC and there has been no significant decrease in the incidence of BDI despite the 40-year period following the first LC surgeries. The incidence of BDI is still lower in OC cases than in LC. Probably the biggest reason for this is the lack of a 3-dimensional view in LCs. Accordingly, manipulations performed in the abdomen with laparoscopic instruments causes more trauma. In fact, the results in BDI cases where laparoscopic surgery is performed by providing a 3-dimensional view are much more successful than OC.

Due to this important handicap of LC, the CVS program should be applied in all cases to avoid bile duct traumas and eliminate risk factors, and the bile ducts should be made visible with various advanced examinations before surgery. However, these surgeries should definitely be performed by experienced surgeons, and great effort should be made to detect BDI injuries during and after surgery for early surgical intervention in BDIs. Because early treatment results are better. Robotic surgery is not yet widely used in routine practice because it requires special personnel and equipment and is expensive.
In difficult cases, LC should not be insisted on and OC should be converted or partial cholecystectomy or top-down cholecystectomy should be performed.

AUTHORS' CONTRIBUTIONS

HZA: Reviewing, analysing and editing; AO: Writing.

CONFLICT OF INTEREST

The authors declare that there have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Research Article

Emotional State Analysis of Duzce University Students Using MODUM Application Data with Data Mining Methods

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ABSTRACT: The academic and social performance of students is significantly impacted by their mental health, which is a pivotal component of public health. It is well-documented that students in universities often undergo substantial psychological and emotional changes that can profoundly impact their daily behaviors and established mental health state. These alterations may manifest as a range of symptoms, including decreased focus and academic performance, as well as potential psychological discomfort and feelings of loneliness. The present study examines the psychological well-being of students at Duzce University in this regard. The study aims to categorize students' emotional states and identify those who could benefit from prompt psychological assistance. To this end, the study employs data mining and text mining techniques. This study was based on data previously collected from MODUM, an application used by Duzce University. To achieve this goal, the study integrates a range of data mining and text mining techniques for the classification of emotional states. The machine learning algorithms employed include Naive Bayes, Random Forest, Decision Tree (J48), Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Logistic Regression. These algorithms were implemented across multiple software environments, such as Python, MATLAB, and R. Additionally, a variety of natural language processing techniques, including Bag of Words, TF-IDF, Word2Vec, and FastText, were used for effective text representation and preprocessing.

KEYWORDS: Data mining, sentiment analysis, text mining, classification.

1. INTRODUCTION

A growing body of research has documented an escalation in students' mental health challenges, attributable to factors such as peer pressure, academic pressure, and the transition to a novel study environment. These elements have had deleterious effects on students' mental and emotional well-being. In order to establish a secure and well-regulated learning environment, it is imperative to closely observe students' mental health and provide the appropriate level of support when necessary. A substantial proportion of programs are predicated on conventional therapeutic modalities that lack a foundation in behavioral analysis or real-time data. In this regard, the present study developed a sophisticated analytical model in which the psychological states of students may be tracked on a daily basis according to interaction with emojis and text communication analysis between students and the support team. The utilization of these algorithms is twofold: firstly, they assist in the classification of emotional states, and secondly, they facilitate the identification of cases necessitating proactive intervention. The objective of this project is to address the issue of "the lack of a smart and precise system to track and analyze the day-to-day psychological status of university students, and more unitarily identify vulnerable students. This predicament exemplifies a salient contemporary limitation of psychological support systems in academic institutions, which often resort to conventional methodologies or questionnaires that prove to be ineffective. The objective of this study is to propose a novel digital solution that higher learning institutions can utilize to make evidence-informed decisions using real-time data. Additionally, a range of sophisticated software programs, including R, MATLAB, and Python, were utilized to execute machine learning algorithms. A comparative intellectual approach was employed to analyze the processing of psychological and textual data, thereby establishing a novel methodological objective for the research. A review of the extant literature reveals that the majority of research in this area utilizes standard analysis tools or paper-based questionnaires, such as standardized questionnaire-based studies. The present study is distinctive in its integration of emoticon symbols and its utilization of the Turkish language, thereby ensuring a greater degree of alignment with actual reality. The present study proposes a practical model for the monitoring of the daily psychological state, the identification of potential data collected from an effective application to university (MODUM), the provision of an immediate categorization system for students requiring psychological support, and the offering of an analysis tool that will be available to Turkish universities for the university support system in the future [1].

The MODUM application was developed with the objective of providing students from all academic departments at Duzce University with assistance. Students are permitted to identify their emotional state by selecting an emoji a total of four times per day. The application provides a selection of nine emojis, and students have the option to request assistance and support from a dedicated team during standard university operating hours. The app's success underscores the importance of providing psychological support to students to enhance their productivity and focus in academic life. The application integrates artificial intelligence and contemporary technological frameworks to optimize its efficacy [1].

Recently, deep learning models, including recurrent neural networks (RNNs) and convolutional neural networks (CNNs), have achieved significant success in numerous domains due to their advanced capabilities in automatic feature representation learning. These models have also been extensively applied in various spatio-temporal data mining (STDM) tasks, such as predictive learning, anomaly detection, and classification. In this paper, we present a thorough examination of recent advancements in the application of deep learning techniques for STDM. The initial step involves the classification of the spatio-temporal data into five distinct categories. Subsequently, an overview of the prevalent deep learning models employed in STDM is provided. In the following section, an analysis of extant literature is conducted with the objective of identifying the types of spatio-temporal data, the data mining tasks, and the deep learning models [2].

Data mining is defined as the process of examining voluminous data sets with the aid of computer technology to discern patterns, trends, and insights. Data mining tools facilitate the prediction of future trends, enabling businesses to make informed, knowledge-driven decisions. The substantial volumes of data produced by conventional methods for predicting heart disease are too intricate and extensive to be efficiently processed and analyzed. The process of data mining provides the technological framework for the transformation of voluminous data sets into actionable information, thereby facilitating informed decision-making. The employment of data mining techniques has been demonstrated to expedite the process of predicting diseases, thereby enhancing the precision of the predictions. This paper presents a survey of studies that utilize data mining algorithms for the purpose of predicting heart disease. The employment of a data mining algorithm to predict future outcomes has been demonstrated to yield highly effective results. The application of data mining techniques to heart disease treatment data has the potential to yield results with a reliability comparable to that observed in prediction and diagnosis of heart disease [3].

This study provides a comprehensive review of state-of-the-art machine learning and data mining techniques used for medical diagnosis and prognosis, including neural networks, K-nearest neighbors (KNN), naïve Bayes, logistic regression, decision trees, and support vector machines (SVM).The findings of the present study demonstrate that neural networks consistently outperform other techniques in terms of diagnostic accuracy and predictive capacity, thereby demonstrating their robustness in handling high-dimensional and nonlinear medical data. This research underscores the potential of advanced machine learning algorithms in revolutionizing early diagnosis and effective prognosis, thus facilitating more personalized treatment plans and improved healthcare outcomes [4].

A pervasive issue that persists throughout students' academic trajectories is their substandard performance in high school. The ability to predict students' academic performance can benefit educational institutions in a variety of ways. Educational institutions can achieve their educational goals by providing support to students earlier in their academic careers. This support can be provided by identifying and understanding the factors that can affect the academic performance of students at the beginning of their academic careers. The objective of this study was to develop a model that could predict the achievement of early secondary students. Two sets of data were utilized for high school students who graduated from the Al-Baha region in the Kingdom of Saudi Arabia. In this study, three models were constructed using different algorithms: The following algorithms were utilized: Naïve Bayes (NB), Random Forest (RF), and J48. Furthermore, the Synthetic Minority Oversampling Technique (SMOTE) was employed to balance the data and extract features using the correlation coefficient. The performance of the prediction models has been validated using 10-fold cross-validation and direct partition, as well as various performance evaluation metrics, including accuracy curve, true positive (TP) rate, false positive (FP) rate, accuracy, recall, F-Measurement, and receiver operating characteristic (ROC) curve. The NB model demonstrated a prediction accuracy of 99.34%, closely followed by the RF model with 98.7% [5].

In this study, we compared several sampling techniques to address the varying ratios of the class imbalance problem (i.e., moderately or extremely imbalanced classifications) using the High School Longitudinal Study of 2009 dataset. To facilitate a comprehensive comparison, a multifaceted resampling approach was employed, encompassing random oversampling (ROS), random undersampling (RUS), and a synthesis of the synthetic minority oversampling technique for nominal and continuous data (SMOTE-NC) in conjunction with RUS, a hybrid resampling technique. The Random Forest was utilized as the classification algorithm to assess the outcomes of each sampling technique. The findings of the present study indicate that random oversampling for moderately imbalanced data and hybrid resampling for extremely imbalanced data appear to be the most effective approaches. The implications for educational data mining applications and suggestions for future research are discussed [6].

Sentiment analysis constitutes a pivotal component within the domain of natural language processing, encompassing the identification of a text's polarity, that is, the presence or absence of positive, negative, or neutral sentiment. The advent of social media and the Internet has led to a marked increase in the importance of sentiment analysis in a variety of fields, including marketing, politics, and customer service. Nevertheless, sentiment analysis poses significant challenges in the context of foreign languages, particularly in the absence of labeled data for training models. In this study, an ensemble model of transformers and a large language model (LLM) is proposed, with the model leveraging sentiment analysis of foreign languages by translating them into English. The languages employed in this study included Arabic, Chinese, French, and Italian, which were translated using two neural machine translation models. LibreTranslate and Google Translate. Subsequently, an ensemble of pre-trained sentiment analysis models was employed to analyze the sentences for sentiment. Twitter-Roberta-Base-Sentiment-Latest, bert-base-multilingual-uncased-sentiment, and GPT-3, which is a language model from OpenAI. The experimental results demonstrated that the accuracy of sentiment analysis on translated sentences exceeded 86% when employing the proposed model. This finding suggests that foreign language sentiment analysis is feasible through translation to English and that the proposed ensemble model outperforms independent pre-trained models and LLM [7].

The proliferation of unstructured data, manifesting as digitized text, is exhibiting a marked increase in terms of both volume and accessibility. Given the potential of text mining as a methodological framework, the primary objective of this manuscript is to empower novice and experienced innovation researchers to select, specify, document, and interpret text mining techniques in a manner that generates valid and reliable knowledge for the innovation management community. To this end, a systematic review of 124 journal articles was conducted, employing text mining techniques and published in a collection of 10 premier innovation management and 8 top general management journals. The results of the systematic manual and computational analysis of these articles illustrate the state and evolution of text mining applications in our field. They also allow for evidence-based recommendations regarding their future use. In this paper, we propose a set of methodological, conceptual, and contextual development priorities that we believe will contribute to establishing higher methodological standards in text mining and enhance the methodological richness in our field [8].

Text embedding models have been utilized in information retrieval applications, such as semantic search and question-answering systems based on retrieval-augmented generation (RAG). These models are typically Transformer models that have been fine-tuned with contrastive learning objectives. A particularly challenging aspect of fine-tuning embedding models pertains to the selection of high-quality hard-negative passages for contrastive learning. In this paper, we introduce a family of positive-aware mining methods that use the positive relevance score as an anchor for effective false negative removal, leading to faster training and more accurate retrieval models. An ablation study is conducted on hard-negative mining methods over their configurations, exploring different teacher and base models. We further demonstrate the efficacy of our proposed mining methods at scale with the NV-Retriever-v1 model, which achieves a score of 60.9 on the MTEB Retrieval (BEIR) benchmark and places first when it is published to the MTEB Retrieval on July 2024 [9].

Music has become an essential medium for the expression of emotions and the enhancement of human social experiences. However, the manual interpretation of emotions in song lyrics is often inaccurate and time-consuming, especially for complex or ambiguous lyrics. This creates a need for an automated system that can improve the accuracy and efficiency of emotion classification in song lyrics. Various algorithms, including K-Nearest Neighbor (K-NN), Naive Bayes Classifier, and Support Vector Machine (SVM), have been employed for the purpose of emotion classification in song lyrics. Preliminary studies have demonstrated that the integration of Support Vector Machine (SVM) with Particle Swarm Optimization (PSO) has been shown to attain an accuracy of up to 90%. In contrast, the application of K-Nearest Neighbor (K-NN) with feature selection has yielded the most optimal f-measure of 66.93%. Notably, the model exhibits superior performance in comparison to K-NN and Naive Bayes. The system implementation is web-based and utilizes the Streamlit framework, enabling users to input lyrics and obtain interactive emotion predictions. This research contributes to the analysis of music emotions and offers an efficient and more accessible alternative for emotion classification in song lyrics [10].

Digital transformation is a process that is causing rapid change around the world, especially in the development of metaverse technology. The advent of metaverse technology has elicited a mixed reception from the public, prompting a need for a thorough examination of public opinion regarding its acceptance or rejection. The objective of this research is to analyze 6,728 public comment data points regarding the metaverse on social media platform X, employing a text mining approach. The objective of this experiment is to identify the most effective text mining algorithm model for sentiment analysis in the metaverse. The findings will offer valuable insights to industry professionals engaged in metaverse development. Specifically, the precision value increased to 94%, the recall value increased to 93%, and the F1-score increased to 95%, as indicated by the confusion matrix. Conversely, the Naïve Bayes algorithm exhibited a comparatively lower accuracy of 91%, while the negative sentiment confusion matrix demonstrated an augmented precision of 87%, a heightened recall of 97%, and an augmented F1-Score of 92%. This enhancement in performance is indicative of the enhanced efficacy of the Naïve Bayes algorithm [11].

2. MATERIAL AND METHOD

The data for this research was provided by Duzce University in Turkey, with the understanding that all data will be kept confidential and secure in accordance with the university's privacy and data protection policies. A comprehensive dataset was collected from all faculties and academic levels. The dataset under study includes the number of emojis selected by students across all academic levels, including undergraduate, graduate, and diploma programs. Participants were able to express their emotional state on four separate occasions throughout the day. The university offers more than 55 undergraduate majors and over 50 associate degree programs across various fields, as well as several master's programs. This extensive selection of educational opportunities contributes to the university's extensive database, which is a valuable resource for researchers and students. The dataset under consideration comprised multiple principal columns, which were subsequently aggregated and examined, as illustrated in the following: The term "bolum" is used to denote a department or area of study.

Education_Level: The educational attainment of the subject is indicated by the following designations: The academic degrees offered at this institution include the Bachelor's, Associate's degrees, Master's, and Doctorate degree.

Each emoji is represented in a separate column, including: peace, anxiety, fear, happiness, anger, disgust, shame, sadness, and confusion. The column presents the number of times students in the major selected the emoji. For instance, a survey of 717 undergraduate Visual Communication Design students revealed a preference for the "anxiety" emoji. The "Total" column is used to indicate the total number of options in the "Emoji" section for each department. The " Positive_feeling_total " column was utilized to denote the aggregate number of positive emojis selected by students of the designated department.

The "Negative_feeling_total" column was utilized to denote the aggregate number of negative emojis selected by the department's students, which might encompass emotions such as sadness, anger, and fear. The mood_class column is a variable that serves to assess the prevailing psychological state of the department. The calculation of this index entails the aggregation of positive and negative feelings and their subsequent comparison. In the event that the negative feelings exceed the total positive feelings, the item is designated as "Negative." Conversely, if the negative feelings surpass the total positive feelings, the item is classified as "Positive."

A data set comprising text-based information from interactions between student-university psychological support team members was collected and subsequently analyzed. The objective of this analysis was to identify sentiment and patterns using text mining methodologies. A set of algorithms was utilized to assess the efficacy of classifying students' emotional states through the use of emojis. The objective of this analysis was to ascertain the most efficacious algorithm in terms of classification accuracy and the ability to support multiple datasets. The following algorithms were selected for inclusion in the study, and the scientific justification for each selection is provided below:

1. Logistic regression is a statistical model that has proven to be both simple and effective. This model is a valuable asset for comprehending the impact of a variable on the determination of a psychological state, offering a clear and readily explicable framework. This model has demonstrated a notable degree of efficacy in predicting binary taxonomic outcomes.
2. Support vector machine (SVM), The selection of SVM was predicated on its capacity to address intricate taxonomic challenges, whether linear or nonlinear, and its adeptness in managing textual data that had been converted into digital formats, such as TF-IDF and word2vec.
3. Random forest method, The proposed algorithm is a combinatory approach that addresses the challenges of overfitting and enhances precision by constructing a set of decision trees internally and then averaging their outputs to generate a predicted output. This approach produces an efficient and reliable method for classifying complex psychological states.
4. Naive Bayes algorithm: The selection of an efficient algorithm that operates with high speed and demonstrates particular efficacy in the analysis of text data is paramount. This is due to the proven effectiveness of the algorithm in text classification based on the fundamental principle of independence of variables.
5. The utilization of J48 decision trees is predicated on their capacity to explain the methods behind decision-making processes through the reiterated partitioning of data. This characteristic renders them more readily interpretable, making it easier to identify key classification variables.
6. Sixth, the focus was on the application of artificial neural networks (ANNs) in the context of deep learning. The objective of this examination was to assess the effectiveness of deep learning in analyzing nonlinear and complex relationships among data, particularly in multidimensional representations of text. This analysis draws parallels with the methods employed by Word2Vec and fastText.

Text mining methods: To analyze the text data from the student conversations with the psychological support team, a number of natural language processing (NLP) methods were employed.

The first method is the Bag of Words (BoW) approach, which is a text data representation technique that counts the number of occurrences of words without regard for their order.

The TF-IDF method is a linguistic analysis technique that facilitates the assessment of the importance of a word within a document by considering its relative frequency within that document in relation to the overall frequency of words.

The third method is Word2Vec, which involves representing words as numerical vectors. This method utilizes a neural network to simulate their semantic relations.

Fourthly, FastText is an extension of Word2Vec that facilitates the analysis of word subscripts, thereby conferring a performance advantage in rich conjugation languages, such as Turkish.

The following tools are used for programming and environment purposes:

The investigation utilized Python as the computer language of choice, employing the Anaconda environment to develop and execute data mining and text analysis algorithms through the utilization of Jupyter Notebook software. The R and MATLAB environments provided additional supplemental statistical and taxonomic analysis.

The performance of the algorithms was evaluated using precise metrics, which include:

a) Accuracy: is defined as the percentage of correctly classified cases out of all cases.

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

Where:
True positives (TPs) are cases that have been accurately categorized as positive.
True Negative (TN): The identification of negative cases that meet the established criteria
A "false positive" (FP) is defined as a positive case that has been incorrectly classified.
False Negative (FN): The term "negative situations" is employed in this text to denote circumstances that have been erroneously designated as such.

b) Precision: This calculation determines the percentage of positive cases that were accurately predicted out of all cases that were projected to be positive.

$$\textbf{Accuracy} = \frac{\textbf{TP} + \textbf{TN}}{\boldsymbol{TP} + \boldsymbol{TN} + \boldsymbol{FP} + \boldsymbol{FN}} \quad \textbf{(2)}$$

c) Recall (Sensitivity): The objective of this analysis is to ascertain the extent to which the model is capable of accurately identifying positive cases. The following calculation method has been employed:

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

d) F1 Score: A thorough evaluation of the model's classification performance was derived from the harmonic mean of precision and recall. The following equation is provided for reference:

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

The employment of a combined methodology enabled the study to provide an accurate and comprehensive evaluation of the psychological well-being of students at all educational levels. This objective was achieved by leveraging the complementary integration of text analytics and statistical data to enhance comprehension of emotional and psychological patterns. Consequently, this enhanced understanding informed psychological support strategies. The data were prepared using statistical analysis tools, employing the following techniques to implement classification algorithms:

Normalization: The objective is to standardize values.

Label Encoding: The objective is to transform categorical data into a numerical format.

The standard Gaussian Naive Bayes model was employed without the necessity for parameter adjustments, as it is a lightweight, fast, and efficient model, especially for text classification. The decision tree algorithm was executed with the following parameters: the splitting criterion was designated as 'entropy,' the maximum tree depth was set at 10, and the minimum number of samples required for node splitting was set at 2. These values were utilized to achieve an equilibrium between complexity and accuracy. In the random forest algorithm, the number of trees was set to 100, referred to as the "n_estimators" parameter.

The maximum depth, designated as max_depth, is set to 10. These parameters were modified to mitigate random bias and enhance the reliability of the results, particularly in the context of numeric data categorized by college and sentiment. In the Support Vector Machine (SVM) algorithm, the kernel type was identified as "linear" and "rbf." The gamma parameter is defined as "scale." In the Logistic Regression algorithm, the optimization method was set to "lbfgs," and the regularization value was determined as follows: The constant C is set to 1.0. This model was utilized in the context of binary classification (positive/negative) for the analysis of both numeric and textual data. In the Artificial Neural Networks (ANN) algorithm, the number of cells in the hidden layer was specified as: hidden_layer_sizes = (100).

The activation function is defined as "relu."

The training algorithm utilizes the "adam" solver.

The maximum number of iterations is set to 200.

The previous values were utilized within a rigorous and repeated training process, with the results being tested on a separate dataset to ensure the reliability of the models.

3. RESULTS

The study's findings encompass two primary components: the categorization of emoji-related statistical information and the sentiment analysis through text mining methodologies. The four primary performance metrics employed for the evaluation of each model were accuracy, precision, recall, and F1 score. The utilization of emoji statistical data for the purpose of classifying students' emotional conditions yielded disparate outcomes, contingent upon the employed algorithm and the designated programming platform. The study's foundation was a substantial dataset comprising student responses, utilizing nine discrete emojis to denote their emotional states. The dataset encompasses a diverse sample of students from various academic institutions and levels of study, providing a substantial and reliable depiction of the emotional landscape of the student body.

The logistic regression model exhibited a commendable capacity to predict cases, attaining a maximum accuracy of 78% and a maximum positive precision of 81%. The Support Vector Machine (SVM) and Random Forest machine learning algorithms exhibited the highest recall rate of 100%, thereby demonstrating their capacity to detect all positive examples without missing any.

The logistic regression model exhibited an optimal balance between positive precision and recall, with an overall F1 value of 86%. The findings suggest that the logistic regression model attained balanced and superior overall performance.

Table 1. Comparison of algorithm performance.

Algorithm	Accuracy	Precision	Recall	F1 Score
Logistic Regression	78%	81%	78%	86%
Support Vector Machine	67%	67%	100%	79%
Random Forest	71%	70%	100%	81%

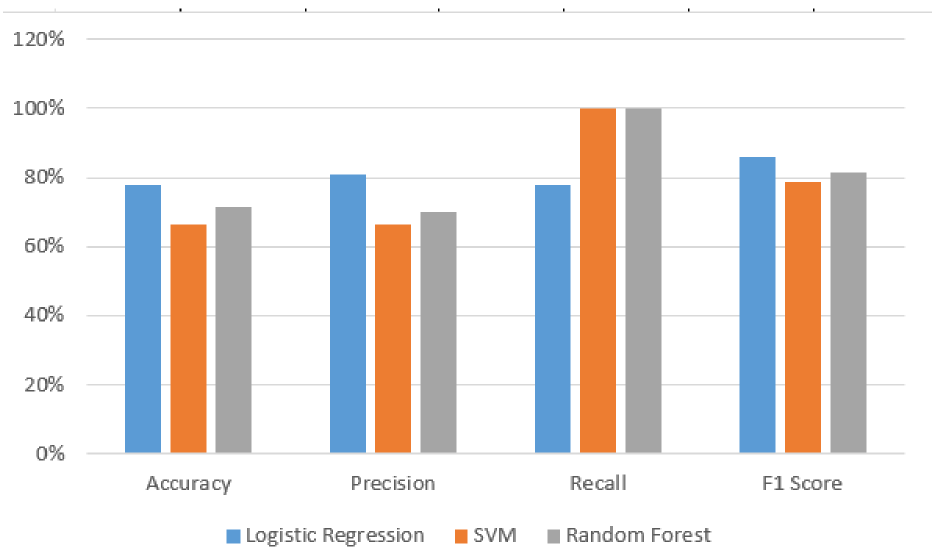

Figure 1. Comparing the performance of classification algorithms.

The SVM and random forest algorithms are particularly advantageous in scenarios where minimizing false negative errors is paramount. The application of sentiment analysis to text has been facilitated by the Python programming language, encompassing a range of text representation techniques, including both Bag of Words and FastText models, along with various classification algorithms. The findings of the study demonstrated that the integration of FastText representation and the Random Forest algorithm yielded the optimal classification accuracy of 100%. This outcome suggests that a state of perfect equilibrium was attained in the overall modeling performance. The combination of FastText and the decision tree algorithm (J48) also achieved the highest positive accuracy overall at 98%, indicating a very good capacity for correctly identifying positive cases. In the context of retrieval, the combination of bag of words with logistic regression emerged as a particularly salient approach, as it demonstrated the highest capacity for identifying relevant cases with exceptional efficiency.

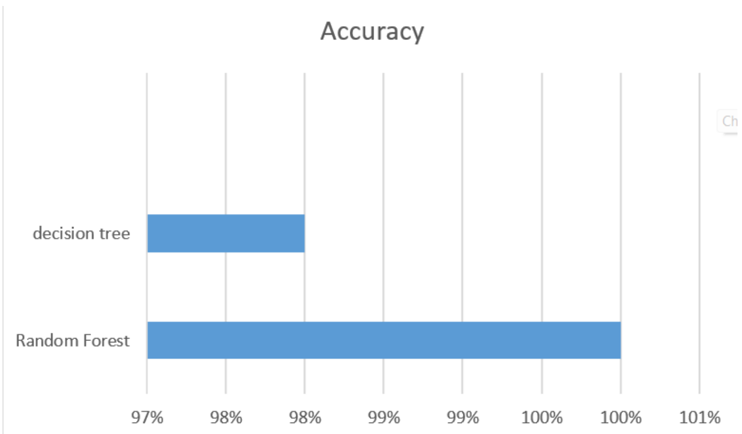

Figure 2. FastText text classifier performance.

The random forest model with bag of words also achieved the highest f1 scale, indicating its effectiveness in achieving a good equilibrium between positive accuracy and retrieval. As anticipated, the findings reveal that FastText representations, characterized by the lowest Root Mean Square Error, yield more precise predictions. However, the Bag of Words representation was found to be more successful in achieving a balance between retrieval and scales, which in turn produced improved accuracy. In the statistical data analysis portion of the study, the logistic regression model in MATLAB demonstrated the highest level of overall accuracy and the greatest F1 score. The SVM and random forest algorithms demonstrated a notable proficiency in looping, making them a particularly suitable option in scenarios where minimizing negative errors is of paramount importance. With regard to text analysis, the FastText representation demonstrated the highest classification efficiency, while the Bag of Words representation showed the greatest improvement in the F1 score and retrieval. This study is subject to several limitations related to the properties of the data utilized, which predominantly centered on emojis and abbreviated text. These factors may have an impact on the comprehensive emotional portrayal of students' experiences. The analysis exclusively incorporated aggregated data, precluding access to data that could have been more individual or chronologically sequenced. This limitation may have constrained our capacity to comprehensively understand the dynamic development of the psyche. The researcher posits that the scope of the study could be expanded in the future to encompass a more extensive array of behaviors. This expansion would facilitate the integration of sophisticated techniques from natural language processing, thereby enabling a more comprehensive and thorough analysis. Furthermore, the integration of multiple behavioral metrics could assist in more accurately identifying various psychological states.

4. CONCLUSION

This research has two important aspects that aim to explore the psychological states of Duzce University students using two different approaches. The first axis classifies the students' emotional states based on the statistical data of the emojis used by students within the mental health support application. The second axis categorizes emotions in conversational texts using text mining and natural language processing tools. The findings indicate that the quality of the input data and the programming environment can significantly impact the performance of categorization algorithms. Algorithms such as Random Forest and SVM demonstrate the highest recovery rates, while other models, including logistic regression, achieve the highest levels of accuracy and F1 score. In the textual emotional analysis, the FastText representation of the data proves to be notable, especially when combined with the Random Forest algorithm, which achieves accuracy rates of up to 100%.

A collegiate-level analysis of the findings shows that students demonstrating optimal psychological stability are predominantly enrolled in the faculties of Business Administration, Mathematics, International Trade, and Mechatronics Engineering. The underlying causes of this phenomenon appear to be multifaceted, including, but not limited to, the curriculum structure, the professional environment of the faculty, and the level of social and psychological support available within each faculty. It is important to underscore that the Departments of Political Science and Public Administration, Forest Engineering, Occupational Health and Safety, and International Relations display substantial indicators of psychological distress. Consequently, the respective faculty administrations, in coordination with mental health professionals, are advised to develop and implement targeted interventions aimed at promoting students' mental well-being. The findings highlight the significance of employing data and text mining methodologies in conjunction with artificial intelligence capabilities to promote mental well-being in academic settings. They emphasize that the caliber of outcomes and their practical application depend on the nature of the data collected and the path followed by the chosen analytical model. This highlights the necessity of identifying and applying scientific practices that align optimally with each study's objective and contextual needs.

In light of the findings and observations from this study, the following recommendations aim to enhance the mental well-being of students and optimize the efficacy of available supportive initiatives within higher education.

The initial step entails the provision of specialized psychological support to the institutions with the highest probability of being affected. The results of the study indicate that students specializing in Media, Forestry, Political Science, and Occupational Health and Safety exhibit a significantly higher prevalence of psychological distress compared to students pursuing other specializations. Therefore, it is recommended that departments within these faculties collaborate with the university’s psychological counseling centers to provide individual consultations, ongoing support sessions, and interventions tailored to students’ needs. The objective of this initiative is to expand the reach of the program to encompass all universities in Turkey. The program’s success in improving student mental well-being at Duzce University suggests its potential applicability to other Turkish higher education institutions, provided that local administrative and cultural differences are carefully considered. This initiative facilitates the establishment of a comprehensive and sustained network of psychological support services. It is imperative to motivate students to proactively and effectively participate in the program. The efficacy of the platform depends on students’ proactive engagement in regular assessments and reports regarding their psychological well-being. Consequently, it is essential to implement awareness initiatives that educate users about the platform’s benefits and its commitment to privacy and data protection. These initiatives should also offer symbolic incentives to encourage regular engagement with the platform. The objective is to establish an environment characterized by amiability and inclusivity within the university setting. In order to alleviate the academic pressures experienced by students, it is imperative that institutions of higher education implement policies mindful of mental health. These policies encompass a range of initiatives, including providing flexible submission deadlines for assignments, incorporating stress and anxiety management courses into the curriculum, and integrating mental health services as a fundamental component of the university’s daily operations, ensuring seamless and direct access for all students.

This study highlights the importance of using data and text mining techniques to effectively assess and support students' mental health. The study also highlights the importance of ongoing monitoring and collaboration between departments and psychological services to promote a healthy and supportive learning environment.

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ETHICAL STANDARD DECLARATION

The necessary permissions were obtained from the Duzce University Ethics Committee to ensure the ethical use of the data collected for this study. The ethics committee approval, dated June 26, 2025, and numbered 588248, is available for review.

DATA AVAILABILITY STATEMENT

The data utilized in the study were obtained with the approval of the relevant ethics committee and in accordance with the principles of confidentiality. The dissemination of data is contingent upon adherence to Duzce University's data privacy and access policies.

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