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Medical Opinions Analysis about the Decrease of Autopsies Using Emerging Pattern Mining

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Abstract: An autopsy is a widely recognized procedure to guarantee ongoing enhancements in medicine. It finds extensive application in legal, scientific, medical, and research domains. However, declining autopsy rates in hospitals constitute a worldwide concern. For example, the Regional Hospital of Rio Blanco in Veracruz, Mexico, has substantially reduced the number of autopsies at hospitals in recent years. Since there are no documented historical records of a decrease in the frequency of autopsy cases, it is crucial to establish a methodological framework to substantiate any actual trends in the data. Emerging pattern mining (EPM) allows for finding differences between classes or data sets because it builds a descriptive data model concerning some given remarkable property. Data set description has become a significant application area in various contexts in recent years. In this research study, various EPM (emerging pattern mining) algorithms were used to extract emergent patterns from a data set collected based on medical experts' perspectives on reducing hospital autopsies. Notably, the top-performing EPM algorithms were iEPMiner, LCMine, SJEP-C, Top-k minimal SJEPs, and Tree-based JEP-C. Among these, iEPMiner and LCMine demonstrated faster performance and produced superior emergent patterns when considering metrics such as Confidence, Weighted Relative Accuracy Criteria (WRACC), False Positive Rate (FPR), and True Positive Rate (TPR).

Keywords: data mining; decrease in autopsies; emerging pattern mining; medical opinions; pattern recognition

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1. Introduction

An autopsy is a recognized procedure to improve the quality of medical work [1]. It is where the pathology specialist conducting it examines a cadaver to determine the main disease causing the death. It is an orderly and meticulous process that includes external examination and the inspection of internal organs. Autopsies are commonly performed for medical, educational, scientific, legal, and research purposes. The practice of this procedure contributes significantly to medical knowledge and the training of medical professionals [2]. Even with that, the decrease in hospital autopsies is a global issue [3], as evidenced by the findings of authors from North and South Korea, who determined that clinical autopsies fell from 0.17% to 0.03% between 2001 and 2015 [4]. According to a study, clinical autopsies in the Netherlands decreased from 31.4% to 7.7% between 1977 and 2011 [5]. Similarly, a separate study unveiled that the overall rate of autopsies experienced a decline of 2.73% from 1991 to 2015 [6]. A 30% decline in total autopsies was observed in Germany between 2005 and 2014 [7]. This percentage exhibited a resemblance to prior findings documented in other nations, including the United States, in particular in major academic medical centers [8], France [9], and Sweden [7]. A decline of 12% in hospital investigations was observed in Australia between 1992 and 2003 [10]. This trend was also observed in other countries [11–14]. Also, at the Regional Hospital of Rio Blanco, situated in the Mexican state of Veracruz, the pathology department identified a considerable reduction in autopsies performed in recent years. The Regional Hospital of Rio Blanco is one of the most important medical centers in the state of Veracruz's central region, offering medical care to more than 1,000,000 inhabitants from the 57 nearby municipalities and even from neighboring states such as Oaxaca and Puebla. Therefore, a survey of medical staff was conducted to determine the main reasons for this decline and establish strategies to increase these studies.

Then, the doctors' answers were analyzed with the use of data mining methods, including Bayesian Networks and association rules [15]. Data mining refers to the utilization of powerful computer science tools to obtain valuable insights from large databases in various domains, including healthcare, scientific research, industry, and many others. Frequently, the key to a successful application is constructing a model from the data, i.e., a concise overview or description of the key aspects of the data [16]. Essentially, descriptive data mining aims to convert unprocessed data into a comprehensible format for humans, thereby facilitating its interpretation [17]. Descriptive tasks aim at deriving correlations, clusters, anomalies, trends, and trajectory patterns that restate the fundamental data relationships. In general, descriptive data mining tasks are observational. They often need techniques for validating and explaining findings [18], such as association rule mining, which identifies recurring patterns, associations, correlations, or causal structures within groups of objects or elements in transactional, relational, and other types of databases. Association rules are generally if–then clauses that are utilized in a relational database or other information repositories to establish relationships between data that appear to be unrelated [19]. In addition, within the data mining field are supervised descriptive rule discovery techniques, which aim to obtain a model that allows for understanding, describing, or finding underlying phenomena of interest in the data. In this field of study, various methods employ rules and supervised learning models to acquire descriptive insights from data that are pertinent, innovative, and engaging to users. These methods encompass subgroup discovery, contrast sets, and emerging pattern mining (EPM) [20].

This study describes the findings of implementing EPM algorithms available within a framework [21] on a data set obtained from a survey conducted among medical practitioners at the Regional Hospital of Rio Blanco to find differences between classes. An EPM algorithm builds a descriptive data model concerning an interesting property. It scans for distinguishing patterns or data elements whose frequency rises considerably from one subset to another. In the last few years, the characterization of data sets has emerged as a compelling field of study across several domains, including healthcare, owing to the convenient accessibility of information for domain specialists [22] (e.g., pathologists). The primary contribution of this work is a comparison of eleven EPM algorithms to select the best one for a medical opinion analysis about the decreasing rates of autopsies conducted at the Regional Hospital of Rio Blanco, considering four attribute class labels corresponding to the reasons that the family of the deceased has to reject the autopsy, the reasons why autopsies are not carried out in the hospital, the staff member's adequacy to request the autopsy, and the motives that the physician has to request an autopsy.

The remaining sections of this paper are arranged in the following order. Section 2 examines the current state of the art. Section 3 includes the analysis of the data set using the EPM framework. Section 4 provides the results. Finally, the conclusions and possible directions for future research are discussed in Section 5.

2. State of the Art

This section presents some approaches related to this work. They applied EPM algorithms to solve problems in several domains like health, chemistry, tourism, and businesses.

Reps et al. [23] applied EPM to find drug and medical event item sets associated with myocardial infarction development. In a study conducted by Davazdahemami and Delen [24], the impact based on the occurrence's prescription sequence of negative medication effects, particularly kidney damage in diabetic patients, was examined. The researchers explored the potential impact of mining for emerging sequential pattern methodologies on electronic health records.

Métivier et al. [25] presented the automatic extraction of potential structural warnings from a set of molecules in the context of predictive toxicology. This method utilizes computer technologies for relationship detection between large biological and chemical data sets containing chemical structures and toxicological activities, employing EPM techniques. Li et al. [26] discovered emerging hotel preferences through the application of EPM. This allowed hotel managers to acquire valuable insights into travelers' interests, enabling them to comprehend swift fluctuations in tourist preferences better. Yu et al. [27] proposed classifying Internet users based on their preferences extracted from web log data. They have proposed an approach that employs EPM techniques. During the mining process, they utilized emerging patterns unique to each web user to distinguish websites that one user frequently accesses but others do not. By identifying rising patterns across every web user, they eliminated the noise inherent in websites for each user, subsequently clustering web visitors based on creating common web pages. In another study, Weng and Huang [28] defined four distinct emerging patterns by combining the concepts of the product life cycle and emerging patterns: patterns of growth, rapid rise, rapid sink, and decline. These patterns were established to identify interesting sales trends. Similarly, Abd-Ellatif et al. [29] used EPM to identify the four fundamental life cycle patterns in financial time series data to help investors make better financial decisions.

A comprehensive overview of EPM was performed by García-Vico et al. [22], where they presented a taxonomy of EPM approaches and a complete empirical study, summarizing future tendencies and rising opportunities in pattern mining, along with the advantages of the knowledge gained from emerging patterns. Also, García-Vico et al. [30] explored numerous quality metric combinations used as optimization objectives in the BD-EFP algorithm (a big data strategy for fuzzy emerging pattern generation) [31] when applied to a range of big data challenges. BD-EFP represents an inaugural multi-objective evolutionary algorithm designed for EPM within big data settings. Similarly, García-Vico et al. [32] introduced a distributed approach according to an evolutionary fuzzy system for extracting and consolidating the emergence of descriptive patterns in data streaming. Additionally, an experimental investigation was conducted to assess the viability of the evolutionary algorithm for extracting high-quality emerging patterns (EPs) and its potential to accommodate a range of concepts. Alternatively, Neto et al. [33] put forward VAX, a visual analysis method that contributes to visual pattern interpretation in multivariate data sets. Jumping emerging patterns were used in VAX to represent relationships coming from decision trees. In addition, the VAX method was validated through real-life use-case data sets.

Rahardja et al. [34] developed a research project focused on using data mining techniques, specifically the supervised emerging patterns method, to analyze and make decisions based on COVID-19 disease data from DKI in Jakarta, Indonesia. According to the Cross-Industry Standard Process for Data Mining (CRISP-DM) model, the research project adheres to a systematic approach. The study's main aim was to create a supervised emerging pattern method that could be used for decision-making purposes using COVID-19 disease data from DKI in Jakarta, specifically focusing on attributes related to status, municipalities, lab results, isolation or treatment status, and age. The methodology followed some essential stages: (1) Data Collection: data were collected from various sources, including the

Corona Jakarta information system and data from http://data.jakarta.go.id (accessed on 19 June 2023); (2) Data Understanding: this stage involves acquiring some comprehension of the data, identifying issues with the data, and forming suppositions for hidden knowledge; (3) Data Preparation: In this stage, the data were cleaned and transformed for modeling. Data integration was performed, combining data from different sources. (4) Modeling: After the emerging patterns, the data mining method was applied, focusing on using two attributes as item sets. The confidence and growth rate were assessed to determine the attractiveness of the patterns. (5) Evaluation: the patterns generated by the model were evaluated, and their appropriateness was assessed based on predefined criteria; and finally, (6) Deployment: the results of the implementation were established using PHP applications to produce pattern reports for the COVID-19 task force's decision-making process. The research highlights the significance of COVID-19 data patterns in determining categories like OTG (asymptomatic), DTG (waiting for results), and positive cases. The practical implication is that this system can assist the COVID-19 task force in formulating policies and preventive measures.

According to [35], cancer ranks as the second leading global cause of mortality, with an estimated projection of 20 million new cases per year by the year 2035. The proliferation of data mining techniques has resulted in several research endeavors focused on using machine learning approaches for early cancer diagnosis. Recently, interest has shifted to using early detection techniques based on deep learning of melanoma via picture analysis. None of this research, however, centered on the descriptive data mining methods necessary for producing more actionable and comprehensible findings. Accurately identifying the genes responsible for developing certain types of cancer is crucial for precise treatment strategies. For this reason, the authors proposed a descriptive analysis based on EPM. Separating cancer genomic data into two categories—cases and controls—would enable them to identify the genes and their expressions linked to each form of cancer, according to their primary hypothesis. The ultimate objective is to tackle the existing obstacles in the well-recognized and established process, generating comprehensible and practical insights that facilitate the exploration of novel and precise approaches to cancer therapy. The suggested methodology was assessed using several real-life circumstances about various forms of cancer. A comprehensive analysis was conducted on six distinct case studies using RNA-Seq data from The Cancer Genome Atlas (TCGA). The findings produced in this study provide evidence for the efficacy of the proposed approach. Several derived findings have already been documented in the relevant literature as promising cancer biomarkers. However, several discoveries have not been previously reported, mainly because current methodologies are influenced by pre-existing information sourced from biological databases.

Although EPM has been applied to solve problems in several domains, to the best of our knowledge, only Ríos-Méndez et al. [36] have used it to analyze medical opinions about the decreasing rates of autopsies in hospitals. The difference between [36] and this work is that in [36], the EPs were obtained considering two class labels, justifications for both requesting and rejecting autopsies, while in this work, four different attribute class labels are taken into account to discover EPs: factors influencing family rejection of autopsy, insufficient autopsy rates in hospital settings, appropriate personnel for autopsy requests, and physician-driven reasons for autopsy requests.

3. Materials and Methods

This section describes the data collection of medical opinions regarding the decline in autopsy frequency conducted at the Regional Hospital Río Blanco and the EPM framework and algorithms. After a thorough examination, the selected methods utilized in this study are discussed.

3.1. Data Set

The data set [15,36] consists of 17 categorical characteristics and a total of 7856 occurrences. Each attribute is shown in Table 1.

Table 1. Attributes of the data set.

Name	Description
Area	The field of medicine
Category	Corresponding class
Ult_grade	Last degree of studies
Gral_med_school	General Medical School
Spec_school	Medical Specialties School
Years_exp	Years of experience in medical practice
Cases	Participation in the cases of autopsy
Finding_disc	Autopsy findings discrepant with clinical diagnosis
Finding_arb	Autopsy findings in arbitration cases
Finding_claims	Autopsy findings arise from claims
Reasons_aut	Reasons for accepting autopsies
Reasons_not_aut	Reasons for not accepting autopsies
Family_refusal	Reasons for family refusal of autopsy
Underperforming_hosp	Reasons for underperforming hospital autopsies
Appropriate_pers	Appropriate personnel for autopsy request
Physician_request	Reasons for physician requesting an autopsy
Efficient_req_met	Efficient autopsy request methods

3.2. EPM-Framework

The EPM-Framework is an openly accessible Java framework designed to facilitate the implementation and execution of EPM algorithms across many data sets [21]. Several EPM algorithms have been implemented in this framework, including EP-Random Forest [37], LCMine (Logical Complex Miner) [38], CEPMine (Crisp Emerging Pattern Mining) [39], EvAEP (Evolutionary Algorithm for Extracting Emerging Patterns) [40], DGCP-Tree (Dynamically Growing Contrast Pattern Tree) [41], SJEP-C (Strong Jumping Emerging Patterns Classifier) [42], Top-k minimal SJEPs (Strong Jumping Emerging Patterns) [43], Tree-based JEP-C (Jumping Emerging Pattern Classifier) [44], iEPMiner (Interesting Emerging Pattern Miner) [45], DeEPS (Decision-making by Emerging Patterns) [46], and BCEP (Bayesian Classification based on Emerging Patterns) [47].

3.3. EPM Algorithms

The data set was run through the eleven algorithms outlined in the previous section, considering as classes the attributes *Physician_request*, *Appropriate_pers*, *Family_refusal*, and *Underperforming_hosp*. The most highly rated algorithms for the characteristics were Tree-based JEP-C, iEPMiner, SJEP-C, LCMine, and Top-k minimal SJEPs.

- Tree-based JEP-C is a highly efficient algorithm designed to discover jumping emerging patterns (JEPs). JEPs are emerging patterns specific to a single class and similar to other discriminative patterns in their role of highlighting class distinctions and facilitating the creation of accurate classifiers [43]. Two aspects characterize tree-based JEP-C [44]: the first is the storage of unprocessed data using a tree-based data structure, and the second objective is the creation of an algorithm for data extraction that operates directly on the data contained in the trees. This approach obtained considerable performance gains over others.
- The iEPMiner algorithm employs a tree data structure for mining interesting emerging patterns, where the chi-squared test is used as a heuristic to optimize and simplify the search process. This strategic use of the chi-squared test enhances the algorithm's speed, making it exceptionally efficient. Notably, the heuristic consistently identifies the majority, namely 90%, of the most interesting emerging patterns (EPs), a

capability sufficient for constructing highly accurate classifiers in various real-world applications [45].
- SJEP-C is a rapid, precise, and simplified classifier based upon parts of strong jumping emerging patterns (SJEPs), a form of JEPs. EPs are considered strong when they are both JEPs and minimal. Minimal EPs, i.e., EPs whose sub-patterns are not EPs, are of particular interest because they typically encompass a limited number of variables. Therefore, SJEPs have both understandability and predictive power [22]. The algorithm's mining process for SJEPs relies on a contrast pattern tree (CP-tree) as its foundational framework. SJEP-C consistently demonstrates reliability, exhibiting high effectiveness in classifying diverse data sets. Remarkably, it often attains superior accuracy compared to other cutting-edge classifiers such as Nave Bayes, Random Forest, and C4.5 [42].
- The Top-k minimal SJEPs algorithm [44] addresses the challenge of efficiently extracting the *k* minimal JEPs that are highly prevalent in each decision class. This result is particularly valuable because traditional JEP discovery can be time-consuming, and pruning with minimal support requires various settings. For improvement, the Top-k Minimal SJEPs method employs a CP-tree to identify strong JEPs. The search space is reduced using the minimum support, and the algorithm dynamically increases this support threshold as it discovers new minimal JEPs. The algorithm verifies the minimality of each newly found JEP in real time instead of at the end of the process. This approach results in considerable time and pattern examination savings, especially when the objective is to determine a limited number of highly compatible JEPs.
- LCMine is an efficient algorithm designed to discover discriminative patterns within training data sets comprising distinct and insufficient data, primarily for supervised classification tasks. This algorithm relies on decision tree induction and incorporates a filtering stage. This filtering stage helps to identify a reduced set of better discriminative attributes for each category. In particular, LCMine has three key features that set it apart: (1) it is not based on a priori discretization when handling numerical attributes, which distinguishes it from the majority of algorithms commonly used to extract discriminative patterns; (2) it utilizes an in-depth description of the regularities; and (3) it employs a filtering method to delete the redundant regularities [38].

4. Experimental Results and Discussion

The results of implementing the algorithms on the surveyed data set are presented in this section. The experiments were carried out on a computer equipped with an Intel® Core™ i7 2.90 GHz processor with 8 GB of RAM. Each algorithm was evaluated using a set of predefined metrics [22].

- Speed. The time in seconds it takes to execute each algorithm. After each algorithm was executed ten times, the average execution time is shown.
- CONF. The precision of a pattern's predictive ability for the positive class is known as its confidence.
- Patterns with confidence > 0.6. In the test data set, EPM-Framework allows for obtaining a file containing patterns with a confidence value larger than 0.6.
- Patterns. Pattern count.
- FPR. The False Positive Rate measures the ratio of incorrectly covered examples compared to the total number of negative examples and must be minimal.
- GR. The Growth Rate is a metric used to characterize emerging patterns. It determines the ratio of positive patterns' support to negative patterns' support, and it is regarded as a pattern's ability to discriminate.
- WRACC. The Weighted Relative Accuracy assesses the compromise between pattern generality and confidence.
- TPR. The True Positive Rate is the ratio of correct examples to the total positive examples.

4.1. Analysis and Discussion of the Data Set Considering as the Class Label to the Attribute Family_refusal

Table 2 compares the efficacy of each algorithm when the first three criteria are considered for the attribute *Family_refusal*. LCMine is the faster algorithm, according to Table 2, but it obtained fewer patterns with a confidence greater than 0.6. In contrast, SJEP-C obtained more EPs with a confidence higher than 0.6, but it is the slower algorithm.

Table 2. First comparison among the EPM algorithms for the attribute *Family_refusal*.

Algorithm	Speed (S)	Patterns with Confidence > 0.6	Patterns
iEPMiner	12	405	405
LCMine	6.9	7	82
SJEP-C	52.5	3752	4944
Top-k minimal SJEPs	19.8	39	44
Tree-based JEP-C	9.8	1060	1288

Table 3 illustrates the findings produced for each algorithm concerning the second criterion, wherein the count of patterns encompasses only those surpassing a confidence threshold of 0.6. As we can see in Table 3, although SJEP-C obtained more EPs, LCMine is the best algorithm for the attribute *Family_refusal* because it found EPs with a lower FPR and a higher WRACC, confidence, and TPR than the other algorithms.

Table 3. The second comparison among the EPM algorithms for the attribute *Family_refusal*.

Algorithm	WRACC	CONF	GR	TPR	FPR	Patterns
iEPMiner	0.4049	0.8830	1	0.0522	0.0048	405
LCMine	0.4136	1	1	0.1046	0	7
SJEP-C	0.2592	0.9647	1	0.0197	0.0005	3752
Top-k minimal SJEPs	0.2791	0.9309	1	0.0438	0.0021	39
Tree-based JEP-C	0.3037	0.9776	1	0.0074	0.0002	1060

In Table 4, we show three of the seven EPs obtained by LCMine for the attribute *Family_refusal* (causes of autopsy rejection by family). As it is depicted in Table 4, every EP shows distinctive characteristics considering the level of agreement of physicians with the idea that autopsy findings can originate in arbitration (*Finding_arb*) or claim cases (*Finging_claims*) and the general medicine training center of the medical staff (*Gral_med_school*), as well as their last grade of studies *(Ult_grade*) and the number of autopsies in which they have participated (*Cases*) among the classes 17d (the autopsy was requested inadequately) and 17f (deficient communication between the physician and the patient and his or her family). These patterns exhibit maximum confidence (1) and minimal complexity with few variables (2), making them valuable for description. Additionally, they are maximal, meaning their larger patterns are not emerging patterns (EPs), ensuring high precision.

Table 4. EPs obtained through LCMine for the attribute *Family_refusal*.

EP	Interpretation
IF *Finding_arb* = 8d AND *Gral_med_school* = c1 THEN 17d	If the doctors disagree that autopsy findings could result in arbitration cases and their general medicine training center is c1, then they believe that the main reason for the family's refusal to perform an autopsy is due to the autopsy being inadequately requested.

Table 4. *Cont.*

EP	Interpretation
IF *Finding_arb* = 8d AND *Ult_grade* = g2 THEN 17f	If the doctors disagree that autopsies can originate in arbitration cases and their last grade of studies is general medicine, then they believe that the main reason why the family refuses to allow an autopsy is due to deficient communication between the physician and the patient and his or her family.
IF *Cases* = 4b AND *Finding_claims* = 11z THEN 17f	If physicians participated in fewer than five autopsies and it is unknown if they recognize that autopsies may originate in cases involving claims, then they conclude that the main reason for the family's refusal to perform an autopsy is due to the deficient communication of the physician with the patient and family.

4.2. Analysis and Discussion of the Data Set Considing as the Class Label to the Attribute Underperforming_hsosp

Table 5 compares the efficacy of each algorithm concerning the initial three criteria for the attribute *Underperforming_hosp*. With a greater degree of confidence than 0.6, SJEP-C acquired more EPs, according to Table 5. Nevertheless, iEPMiner is the faster algorithm, and all their EPs exceed 0.6 in confidence.

Table 5. First comparison among the EPM algorithms for the attribute *Underperforming_hosp*.

Algorithm	Speed (S)	Patterns with Confidence > 0.6	Patterns
iEPMiner	3	63	63
LCMine	6.4	14	61
SJEP-C	64.3	6383	8383
Top-k Minimal SJEPs	43.5	29	55
Tree-based JEP-C	10.3	741	973

The findings derived from each algorithm are presented in Table 6 for the second criterion, taking into account that the count of patterns includes exclusively those that surpass the value of 0.6 in terms of confidence. As we can see in Table 6, iEPMiner is the best algorithm for the attribute *Underperforming_hosp* because its EPs have more WRACC and TPRs than the EPs of the other algorithms. Although LCMine found EPs with more confidence and less FPRs than iEPMiner, the latter yielded more EPs.

Table 6. The second comparison among the EPM algorithms for the attribute *Underperforming_hosp*.

Algorithm	WRACC	CONF	GR	TPR	FPR	Patterns
iEPMiner	0.3236	0.8425	1	0.1227	0.0039	63
LCMine	0.2261	1	1	0.0089	0	14
SJEP-C	0.1474	0.9524	1	0.0338	0.0004	6383
Top-k minimal SJEPs	0.2461	0.8920	1	0.0703	0.0024	29
Tree-based JEP-C	0.2144	0.9916	1	0.0115	0.0001	741

In Table 7, we show two of the sixty-three EPs obtained through iEPMiner, one for different class values, in this case, *Underperforming_hosp* (reasons why autopsies are not performed in hospitals). As we can see in Table 7, every EP shows distinct characteristics considering the years of experience of the physicians (*Years_exp*), the number of cases in which they have participated (*Cases*), their last grade obtained (*Ult_grade*), the category of their invitation to answer the survey (*Category*), their level of agreement with the idea that autopsies can originate in claim cases (*Finding_claims*), and the reason why they think families reject autopsies (*Family_refusal*) among the classes 18c (deficient financial resources) and 18d (autopsies are not requested). These patterns have a high confidence value (1 and 0.7402, respectively) and are minimal, so they have few variables (3) and are remarkable for description. Moreover, they are maximal, and therefore, they are very precise.

Table 7. EPs obtained with iEPMiner.

EP	Interpretation
IF *Years_exp* = 3a AND *Cases* = 4a AND *Ult_grade* = g2 THEN 18c	If the doctors have experience of fewer than five years, they were involved in zero autopsy cases, and their last grade obtained is general medicine, then they believe that one reason why the institution does not undertake enough autopsies is a deficiency in financial resources.
IF *Category* = c2 AND *Finding_claims* = 11b AND *Family_refusal* = 17f THEN 18d	If the doctors answer the survey through an intern invitation, they acknowledge that autopsies may originate in cases involving claims, and they believe that the main cause of the family's refusal to perform an autopsy is due to the deficient communication of the physician with the patient and family, then they believe that one reason why there are not enough autopsies carried out in hospitals is due to autopsies not being requested.

4.3. Analysis and Discussion of the Data Set Considering as the Class Label to the Attribute Appropriate_pers

The efficacy of each algorithm is compared in Table 8, taking into account the first three criteria for the attribute *Appropriate_pers*. LCMine is the faster algorithm according to Table 8. Nevertheless, more EPs were obtained with tree-based JEP-C with confidence levels above 0.6.

Table 8. First comparison among the EPM algorithms for the attribute *Appropriate_pers*.

Algorithm	Speed (S)	Patterns with Confidence > 0.6	Patterns
iEPMiner	185.5	1372	1372
LCMine	8	29	174
SJEP-C	135	6080	6168
Top-k minimal SJEPs	29.6	15	33
Tree-based JEP-C	30.7	6095	6252

Table 9 displays the results obtained with each algorithm for the second criterion, with the number of patterns limited to those with a confidence value greater than 0.6. As shown in Table 9, LCMine is the best algorithm for the attribute *Appropriate_pers* because it obtained EPs with more GRs and fewer FPRs compared to other algorithms. Top-k minimal SJEPs had good results concerning GRs and TPRs; nevertheless, the number of patterns of LCMine was higher.

Table 9. The second comparison among the EPM algorithms for the attribute *Appropriate_pers*.

Algorithm	WRACC	CONF	GR	TPR	FPR	Patterns
iEPMiner	0.8039	0.9698	0.9781	0.0615	0.0148	1372
LCMine	0.7254	0.9701	1	0.0203	0.0003	29
SJEP-C	0.6385	0.9880	0.9899	0.0267	0.0020	6080
Top-k minimal SJEPs	0.6258	0.9739	1	0.0821	0.0007	15
Tree-based JEP-C	0.7894	0.9751	0.9529	0.0110	0.0048	6095

Table 10 shows two of the twenty-nine EPs obtained with LCMine, one for different class values, in this case, *Appropriate_pers* (adequate medical staff to request the autopsy).

Table 10 indicates that every EP shows distinct characteristics involving the years of experience of the medical staff (*Years_exp*), the number of autopsy cases in which they have participated (*Cases*), and their level of agreement with the idea that autopsy findings can cause discrepancies with the clinical diagnoses (*Finding_disc*) among classes 19a (physician) and 19e (family). These patterns are precise because they are maximal and possess the most significant degree of confidence (1). Also, they are interesting for the description because they are minimal (both EPs have only three variables).

Table 10. EPs obtained with LCMine for the attribute *Appropriate_pers*.

EP	Interpretation
IF *Years_exp* = 3d AND *Cases* = 4a AND *Finding_disc* = 7b THEN 19a	If the doctors have 16–20 years of practice, they have participated in 0 autopsy incidents, and they agree that an autopsy can cause discrepancies with the clinical diagnoses, then they consider that the appropriate personnel to properly ask for an autopsy is the physician.
IF *Years_exp* = 3d AND *Cases* = 4c AND *Finding_disc* = 7b THEN 19e	If the doctors have 16–20 years of practice, they have participated in 6–10 autopsy incidents, and they agree that autopsy can cause discrepancies with the clinical diagnoses, then they consider that the suitable people to request an autopsy is family.

4.4. Analysis and Discussion of the Data Set Considering as the Class Label to the Attribute Physician_request

Table 11 compares the efficacy of each algorithm concerning the attribute *Physician_request* and the first three criteria. iEPMiner is the faster algorithm, according to Table 11. Nevertheless, more EPs were obtained with SJEP-C with a confidence level exceeding 0.6.

Table 11. First comparison among the EPM algorithms for the attribute *Physician_request*.

Algorithm	Speed (S)	Patterns with Confidence > 0.6	Patterns
iEPMiner	**5**	**153**	**153**
LCMine	6.3	5	133
SJEP-C	59.4	3220	3410
Top-k minimal SJEPs	52.2	26	44
Tree-based JEP-C	10.8	780	987

Table 12 displays the results obtained with each algorithm for the second criterion, with the number of patterns restricted to those with a confidence value over 0.6. As we can see in Table 12, LCMine is the best algorithm for the attribute *Physician_request* because it obtained EPs with more WRACC and confidence. Moreover, lower FPR EPs were produced with LCMine compared to the other algorithms.

Table 12. The second comparison among the EPM algorithms for the attribute *Physician_request*.

Algorithm	WRACC	CONF	GR	TPR	FPR	Patterns
iEPMiner	0.3410	0.8792	1	0.0570	0.0042	153
LCMine	0.3989	1	1	0.0289	0	5
SJEP-C	0.3179	0.9582	1	0.0225	0.0007	3220
Top-k minimal SJEPs	0.3235	0.9479	1	0.0474	0.0028	26
Tree-based JEP-C	0.3789	0.9916	1	0.0044	0.0001	780

In Table 13, we show the 5 EPs obtained with LCMine for the class *Physician_request* (motives of the physicians to request the autopsy). As we can see in Table 13, each EP demonstrates distinguishable attributes regarding the years of experience of the physicians (*Years_exp*), the number of cases in which they have participated (*Cases*), their area (internal, assigned, or resident), their level of agreement with the idea that autopsy findings can originate arbitration (*Finding_arb*) or claim (*Finding_claims*) cases, or discrepancies with the clinical diagnoses (*Find_disc*), and their medical specialty training center (*Spec_school*) within the classes 20a (Interest) and 20e (flawed diagnosis). Being minimal in number and characterized by few variables (three and two), these patterns possess maximum confidence (1), making their description particularly compelling. Moreover, they are maximal; therefore, they are very precise.

Table 13. EPs obtained with LCMine for the attribute *Physician_request*.

EP	Interpretation
IF *Years_exp* = 3e AND *Finding_arb* = 8c AND *Cases* = 4e THEN 20a	If the doctors have more than 20 years of practice, they think that it is uncertain that an autopsy can initiate arbitration cases, and they have been involved in over 20 cases of autopsy, then interest is regarded as a potential factor that could motivate a physician to request an autopsy.
IF *Finding_arb* = 8c AND *Area* = a3 AND *Cases* = 4e THEN 20a	If the doctors think that it is uncertain that an autopsy can originate in arbitration cases, they are assigned, and they have participated in at least 20 autopsies, then they believe that one cause for the physician to request an autopsy is interest.
IF *Years_exp* = 3e AND *Finding_arb* = 8c AND *Finding_disc* = 7c THEN 20a	If the doctors have more than 20 years of practice, they think that it is uncertain that an autopsy can originate in arbitration cases, and they believe that it is uncertain that an autopsy can cause discrepancies with the clinical diagnoses, then they think that one reason for the doctor's request for an autopsy is interest.
IF *Finding_arb* = 8c AND *Area* = a3 AND *Finding_disc* = 7c THEN 20a	If the doctors think that it is uncertain that an autopsy can originate in arbitration cases, they are assigned, and they think that it is uncertain that an autopsy can cause discrepancies with the clinical diagnoses, then they consider that one cause for the physician to request an autopsy is interest.
IF *Finding_claims* = 11a AND *Spec_school* = c7 THEN 20e	If the doctors agree that autopsies can originate in claim cases and their medical specialty training center is c7, then they believe that one cause of the doctor requesting an autopsy is a flawed diagnosis.

Finally, Table 14 shows the best EPM algorithm for each attribute. Although SJEP-C and Tree-based JEP-C obtained more EPs than the other algorithms, LCMine was the best algorithm for three attributes, and iEPMiner was the best for one considering the average WRACC, confidence, TPR, and FPR. iEPMiner and LCMine were also faster than the other EPM algorithms.

Table 14. Best EPM algorithms.

Attribute	The Algorithm That Found More Patterns	Fastest Algorithm
Family_refusal	SJEP-C	LCMine
Underperforming_hosp	SJEP-C	iEPMiner
Appropriate_pers	Tree-based JEP-C	LCMine
Physician_request	SJEP-C	iEPMiner

LCMine found emerging patterns that relate the medical opinions about the appropriate personal staff to request the autopsies and their motives to request this study with factors such as the years of experience of the physicians, the number of autopsy cases in which they have participated, and their level of agreement with the idea that autopsies can cause discrepancies with the clinical diagnoses.

An aspect that restricts the scope of this research is the utilization of the survey exclusively within a single federal and public hospital in Veracruz, Mexico. Despite the institution's possession of a pathology department and the ability to accommodate residents in this field, adequate financial means are absent to enhance its educational offerings. Consequently, the physicians' judgments are influenced, at least partially, by their prior medical experience and academic training at other medical facilities. Nevertheless, it was observed that the participants were affiliated with various academic institutions, thereby allowing us to acquire distinct viewpoints regarding this issue. The survey design exclusively considers medical autopsies, which is an additional constraint of this study. Despite their significance, forensic autopsies fall outside the purview of this work, as the prosecutors' offices in Mexico designate their execution sites. As a result, medical practitioners lack knowledge regarding their instructional approaches, goals, and methodologies. Notwithstanding this, it was ascertained through the examination of the survey data that substantial ambiguity exists regarding the distinction between these two categories of autopsies.

5. Conclusions

Despite the importance of autopsies for medical work, pathologists in Mexican hospitals are facing the global problem of declining autopsy rates. Therefore, the objective of this study was to obtain insights about (1) the reasons, motives, and circumstances that physicians of the Regional Hospital of Rio Blanco have to request an autopsy; (2) the causes of autopsy refusal by the families of the deceased patients; (3) why not enough autopsies are performed in the hospital; and (4) the appropriate hospital staff to request an autopsy according to the doctors. To achieve this goal, we applied eleven EPM algorithms provided by the EPM framework to a data set of medical opinions regarding the decline in the number of autopsies performed at the Regional Hospital of Rio Blanco. The most effective EPM algorithms were Tree-based JEP-C, SJEP-C, Top-k minimal SJEPs, iEPMiner, and LCMine. iEPMiner and LCMine were the faster algorithms, and they obtained better EPs considering WRACC, confidence, the TPR, and the FPR.

In the future, this survey will be conducted at a different facility that can accept medical residents, and the results will be compared using EPM. Then, an EPM module will be implemented in a web application to compare medical opinions about the reduction in autopsies performed in hospitals. The EMP module will use the algorithms iEPMiner and LCMine, given their excellent performance for this task. Also, other supervised descriptive rule discovery techniques will be used to analyze the medical opinions data set, such as subgroup discovery and contrast set mining.

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References

1. Hurtado de Mendoza Amat, J. La autopsia como garantía de calidad en la medicina. *Rev. Cuba. Salud Pública* **2017**, *43*, 468–469.
2. Coradazzi, A.L.; Morganti, A.L.C.; Montenegro, M.R.G. Discrepancies between clinical diagnoses and autopsy findings. *Braz. J. Med. Biol. Res.* **2003**, *36*, 385–391. [CrossRef] [PubMed]
3. Suleiman, D. Reviving hospital autopsy in Nigeria: An urgent call for action. *Ann. Niger. Med.* **2015**, *9*, 39. [CrossRef]
4. Park, J.P.; Kim, S.H.; Lee, S.; Yoo, S.H. Changes in Clinical and Legal Autopsy Rates in Korea From 2001 to 2015. *J. Korean Med. Sci.* **2019**, *34*, e301. [CrossRef] [PubMed]
5. Blokker, B.M.; Weustink, A.C.; Hunink, M.G.M.; Oosterhuis, J.W. Autopsy rates in the Netherlands: 35 years of decline. *PLoS ONE* **2017**, *12*, e0178200. [CrossRef] [PubMed]
6. Latten, B.G.H.; Overbeek, L.I.H.; Kubat, B.; zur Hausen, A.; Schouten, L.J. A quarter century of decline of autopsies in the Netherlands. *Eur. J. Epidemiol.* **2019**, *34*, 1171–1174. [CrossRef] [PubMed]
7. Waidhauser, J.; Martin, B.; Trepel, M.; Markl, B. Can low autopsy rates be increased? Yes, we can! Should postmortem examinations in oncology be performed? Yes, we should! A postmortem analysis of oncological cases. *Virchows Arch.* **2021**, *478*, 301–308. [CrossRef] [PubMed]
8. Sinard, J.H. Factors Affecting Autopsy Rates, Autopsy Request Rates, and Autopsy Findings at a Large Academic Medical Center. *Exp. Mol. Pathol.* **2001**, *70*, 333–343. [CrossRef]
9. Chariot, P.; Witt, K.; Pautot, V.; Porcher, R.; Thomas, G.; Zafrani, E.S.; Lemaire, F. Declining Autopsy Rate in a French Hospital Physicians' Attitudes to the Autopsy and Use of Autopsy Material in Research Publications. *Arch. Pathol. Lab. Med.* **2000**, *124*, 739–745. [CrossRef]
10. Davies, D.J.; Graves, D.J.; Landgren, A.J.; Lawrence, C.H.; Lipsett, J.; MacGregor, D.P.; Sage, M.D. The decline of the hospital autopsy: A safety and quality issue for healthcare in Australia. *Med. J. Aust.* **2004**, *180*, 281–285. [CrossRef]
11. Kunz, S.N.; Bergsdóttir, Þ.; Jónasson, J.G. Autopsy rates in Iceland. *Scand. J. Public Health* **2019**, *48*, 486–490. [CrossRef] [PubMed]
12. Bhatt, M.; Movaseghigargari, M.; Chand, M.T. The importance of autopsies despite the declining number amidst the COVID-19 pandemic. *Autops. Case Rep.* **2022**, *12*, e2021371. [CrossRef] [PubMed]
13. Kalra, J.; Macpherson, J. The Decline of the Hospital Autopsy: A Missed Opportunity for Quality and Education in Healthcare. *Austin J. Clin. Pathol.* **2015**, *2*, 1024.
14. Kapusta, N.D.; Tran, U.S.; Rockett, I.R.; De Leo, D.; Naylor, C.P.; Niederkrotenthaler, T.; Voracek, M.; Etzersdorfer, E.; Sonneck, G. Declining Autopsy Rates and Suicide Misclassification: A Cross-national Analysis of 35 Countries. *Arch. Gen. Psychiatry* **2011**, *68*, 1050–1057. [CrossRef] [PubMed]
15. Rubio Delgado, E.; López-Chau, A.; Cervantes, J.L.S.; Cervantes, J.; Palet Guzmán, J.A.; Peláez-Camarena, S.G.; López-Chau, A. Analysis of Medical Opinions about the Nonrealization of Autopsies in a Mexican Hospital Using Association Rules and Bayesian Networks. *Sci. Program.* **2018**, 4304017. [CrossRef]
16. Leskovec, J.; Rajaraman, A.; Ullman, J. *Mining of Massive Data Sets*, 3rd ed.; Standford University: Stanford, CA, USA, 2019.
17. Han, J.; Kamber, M.; Pei, J. *Data Mining: Concepts and Techniques*; Elsevier: Boston, MA, USA, 2012.
18. Tan, P.N.; Steinbach, M.; Karpatne, A.; Vipin, K. *Introduction to Data Mining*; Pearson: New York, NY, USA, 2019.
19. Bhatia, P. *Data Mining and Data Warehousing: Principles and Practical Techniques*, 1st ed.; Cambridge University Press: Cambridge, UK, 2019.
20. Carmona, C.J.; Jesus, M.J.; Herrera, F. Atipicidad: Medida de calidad clave dentro del descubrimiento de reglas descriptivas supervisadas. In Proceedings of the XVIII Conferencia de la Asociación Española para la Inteligencia Artificial, IX Simposio de Teoría y Aplicaciones de la Minería de Datos, Granada, Spain, 23–26 October 2018; pp. 827–828.
21. GitHub—SIMIDAT/Epm-Framework: A Framework to Easy Execute Emerging Pattern Mining (EPM) Algorithms. Available online: https://github.com/SIMIDAT/epm-framework (accessed on 29 August 2023).
22. García-Vico, A.M.; Carmona, C.J.; Martín, D.; García-Borroto, M.; del Jesus, M.J. An overview of emerging pattern mining in supervised descriptive rule discovery: Taxonomy, empirical study, trends, and prospects. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2017**, *8*, e1231. [CrossRef]
23. Reps, J.M.; Aickelin, U.; Hubbard, R.B. Refining adverse drug reaction signals by incorporating interaction variables identified using emergent pattern mining. *Comput. Biol. Med.* **2016**, *69*, 61–70. [CrossRef]

24. Davazdahemami, B.; Delen, D. Examining the effect of prescription sequence on developing adverse drug reactions: The case of renal failure in diabetic patients. *Int. J. Med. Inform.* **2019**, *125*, 62–70. [CrossRef]
25. Métivier, J.P.; Lepailleur, A.; Buzmakov, A.; Poezevara, G.; Crémilleux, B.; Kuznetsov, S.O.; Le Goff, J.; Napoli, A.; Bureau, R.; Cuissart, B. Discovering Structural Alerts for Mutagenicity Using Stable Emerging Molecular Patterns. *J. Chem. Inf. Model.* **2015**, *55*, 925–940. [CrossRef]
26. Li, G.; Law, R.; Vu, H.Q.; Rong, J.; Zhao, X.R. Identifying emerging hotel preferences using Emerging Pattern Mining technique. *Tour. Manag.* **2015**, *46*, 311–321. [CrossRef]
27. Yu, X.; Li, M.; Kim, K.; Chung, J.; Ryu, K. Emerging pattern-based clustering of web users utilizing a simple page-linked graph. *Sustainability* **2016**, *8*, 239. [CrossRef]
28. Weng, C.-H.; Huang, T. Observation of sales trends by mining emerging patterns in dynamic markets. *Appl. Intell.* **2018**, *48*, 4515–4529. [CrossRef]
29. Abd-Ellatif, L.; Kamel, N.; Abd-Ellatif, M. Efficient Model for Mining Emerging Patterns in Financial Transitions. *Int. J. Eng. Sci.* **2023**, *12*, 13–23.
30. García-Vico, Á.M.; González, P.; Carmona, C.J.; del Jesus, M.J. Study on the use of different quality measures within a multi-objective evolutionary algorithm approach for emerging pattern mining in big data environments. *Big Data Anal.* **2019**, *4*, 1–15. [CrossRef]
31. García-Vico, Á.M.; González, P.; Carmona, C.J.; del Jesus, M.J. A Big Data Approach for the Extraction of Fuzzy Emerging Patterns. *Cogn. Comput.* **2019**, *11*, 400–417. [CrossRef]
32. García-Vico, M.; Carmona, C.J.; González, P.; del Jesus, M.J. A distributed evolutionary fuzzy system-based method for the fusion of descriptive emerging patterns in data streams. *Inf. Fusion* **2023**, *91*, 412–423. [CrossRef]
33. Neto, M.P.; Paulovich, F.V. Multivariate Data Explanation by Jumping Emerging Patterns Visualization. *IEEE Trans. Vis. Comput. Graph.* **2022**, 1–16. [CrossRef]
34. Rahardja, U.; Dewanto, I.J.; Djajadi, A.; Candra, A.P.; Hardini, M. Analysis of COVID 19 Data in Indonesia Using Supervised Emerging Patterns. *APTISI Trans. Manag. (ATM)* **2022**, *6*, 91–101. [CrossRef]
35. Trasierras, A.M.; Luna, J.M.; Ventura, S. Improving the understanding of cancer in a descriptive way: An emerging pattern mining-based approach. *Int. J. Intell. Syst.* **2022**, *37*, 2822–2848. [CrossRef]
36. Rios-Mendez, I.A.; Rodriguez-Mazahua, L.; Guzman, J.A.P.; Machorro-Cano, I.; Pelaez-Camarena, S.G.; Romero-Torres, C.; Muñoz-Contreras, H. Discovering Emerging Patterns from Medical Opinions about the Decrease of Autopsies Performed in a Mexican Hospital. In Proceedings of the IEEE International Conference on Automation Science and Engineering, Hong Kong, China, 20–24 August 2020; pp. 798–803.
37. Wang, L.; Wang, Y.; Zhao, D. Building Emerging Pattern (EP) random forest for recognition. In Proceedings of the International Conference on Image Processing, ICIP, Hong Kong, China, 26–29 September 2010; pp. 1457–1460.
38. García-Borroto, M.; Martínez-Trinidad, J.F.; Carrasco-Ochoa, J.A.; Medina-Pérez, M.A.; Ruiz-Shulcloper, J. LCMine: An efficient algorithm for mining discriminative regularities and its application in supervised classification. *Pattern Recognit.* **2010**, *43*, 3025–3034. [CrossRef]
39. García-Borroto, M.; Martínez-Trinidad, J.F.; Carrasco-Ochoa, J.A. A New Emerging Pattern Mining Algorithm and Its Application in Supervised Classification. In *Advances in Knowledge Discovery and Data Mining*; Zaki, M.J., Yu, J.X., Ravindran, B., Pudi, V., Eds.; Springer: Berlin/Heidelberg, Germany, 2010; pp. 150–157.
40. García-Vico, A.M.; Montes, J.; Aguilera, J.; Carmona, C.J.; del Jesus, M.J. Analysing concentrating photovoltaics technology through the use of emerging pattern mining. In *Advances in Intelligent Systems and Computing*; Graña, M., López-Guede, J., Etxaniz, O., Herrero, Á., Quintián, H., Corchado, E., Eds.; Springer: Cham, Switzerland, 2017; Volume 527, pp. 334–344.
41. Liu, Q.; Shi, P.; Hu, Z.; Zhang, Y. A novel approach of mining strong jumping emerging patterns based on BSC-tree. *Int. J. Syst. Sci.* **2014**, *45*, 598–615. [CrossRef]
42. Fan, H.; Ramamohanarao, K. Fast discovery and the generalization of strong jumping emerging patterns for building compact and accurate classifiers. *IEEE Trans. Knowl. Data Eng.* **2006**, *18*, 721–737. [CrossRef]
43. Terlecki, P.; Walczak, K. Efficient discovery of top-K minimal jumping emerging patterns. In *Lecture Notes in Computer Science*; Chan, C.C., Grzymala-Busse, J.W., Ziarko, W.P., Eds.; Springer: Berlin/Heidelberg, Germany, 2008; pp. 438–447.
44. Bailey, J.; Manoukian, T.; Ramamohanarao, K. Fast algorithms for mining emerging patterns. In *Lecture Notes in Computer Science*; Elomaa, T., Mannila, H., Toivonen, H., Eds.; Springer: Berlin/Heidelberg, Germany, 2002; pp. 39–50.
45. Fan, H.; Ramamohanarao, K. Efficiently mining interesting emerging patterns. In *Lecture Notes in Computer Science*; Dong, G., Tang, C., Wang, W., Eds.; Springer: Berlin/Heidelberg, Germany, 2003; pp. 189–201.
46. Li, J.; Dong, G.; Ramamohanarao, K.; Wong, L. Deeps: A new instance-based lazy discovery and classification system. *Mach. Learn.* **2004**, *54*, 99–124. [CrossRef]
47. Fan, H.; Ramamohanarao, K. A Bayesian approach to use emerging patterns for classification. In Proceedings of the ADC '03: Proceedings of the 14th Australasian Database Conference, Adelaide, Australia, 17 January 2003; pp. 39–48.