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ON THE CONSTRUCTIVE KNOWLEDGE-BASED EVENT INTELLIGENT IDENTIFICATION MECHANISM

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ABSTRACT

The tenor of Complex Event Processing (CEP) is overly exploited to notice endurable information from the latent knowledge flow. Within this research, we provide associate degree creative methodology of CEP so as to achieve a fully developed level of process patterns or events counting on the constructive feature computing. We presented constructive event detection technique to find situations when the event's statute has transferred over a special event to a complex event by generating an emphasis centerpiece to components of complex interconnection by utilizing stacked bidirectional Long Short-Term Memory (LSTM) networks. The Constructive Knowledge-based Event (CKE) detection method tested on the data set provides over 90% of the special events hit rate of the Saturn/Cassini-Huygens interplanetary project. This approach empowers analyses of vast volumes of data within a small-time interval.

Keywords: *Artificial Intelligence, Complex Event, Data Analytics, Constructive Knowledge-Based Event*

1. INTRODUCTION

Observation of complex events illustrating ensnares the capacity to decide on the continuing data if the progressing information stream can be coordinated into the available delineation and how it influences the comprehensive occasions' delineation. There is an expanding need for data systems to handle tireless data streams and respond to specific circumstances. CEP incorporates different information sources to identify and address critical complex events among extraordinary events stream depending on unique modalities. A massive volume of events is vague; the outline of event processing imposes the expediency to clear out the indecision [1]. Cognitive reasoning and computing are an up-growing scope of computing suitable to conquer the potential issues that will show up in CEP frameworks [2].

Among the contribution, we show that CEP is associated with identifying complex events focused on domain specialist rules and trends. The constructive Knowledge-based Event (CKE) algorithm can better analyze vast volumes of data within a small-time interval. Using relevant information regarding events and their relationships in the application environment will enhance CEP systems' expressiveness and versatility. Massive volumes of domain history information contained in an external knowledge base may be used in conjunction with event processing to accomplish more competent, dynamic, constructive knowledge-based event.

Affected by the human cerebrum, subjective computing is advanced based on a cross-theme investigation and inquiry about the scope of cognitive data knowledge and the development of 'thinking' computer systems [3]. A different denomination of a robust framework monitoring task that requires existing observational cogitation to discover the intermittent arrangement of obscure systems has been germane to the most recent instructive-related inquiries about the surge of robust framework control [4]. In any case of their singularity, complex frameworks reiterate and generate what could be a predominant cause for logical realization: the quandary of creating a model that can distinguish fundamental viewpoint or designs from a specific prepare or event [5]. So ready to deduce that constructive modeling might be characterized as a field of computers that deals with emulated human troublesome or complex generate mental preparing and arrangement finding inside a computerized worldview. Constructive modeling investigates and is coordinated toward the theoretical scholarly concept and industry category.

Front line exploitation of constructive modeling is the generation of constructive machines, which may well be portrayed as artificial insights programs that limit human cognition's limit domains. accessible on the Internet. The existing approaches of event processing are transacting essentially with low-level indicators, events stream.

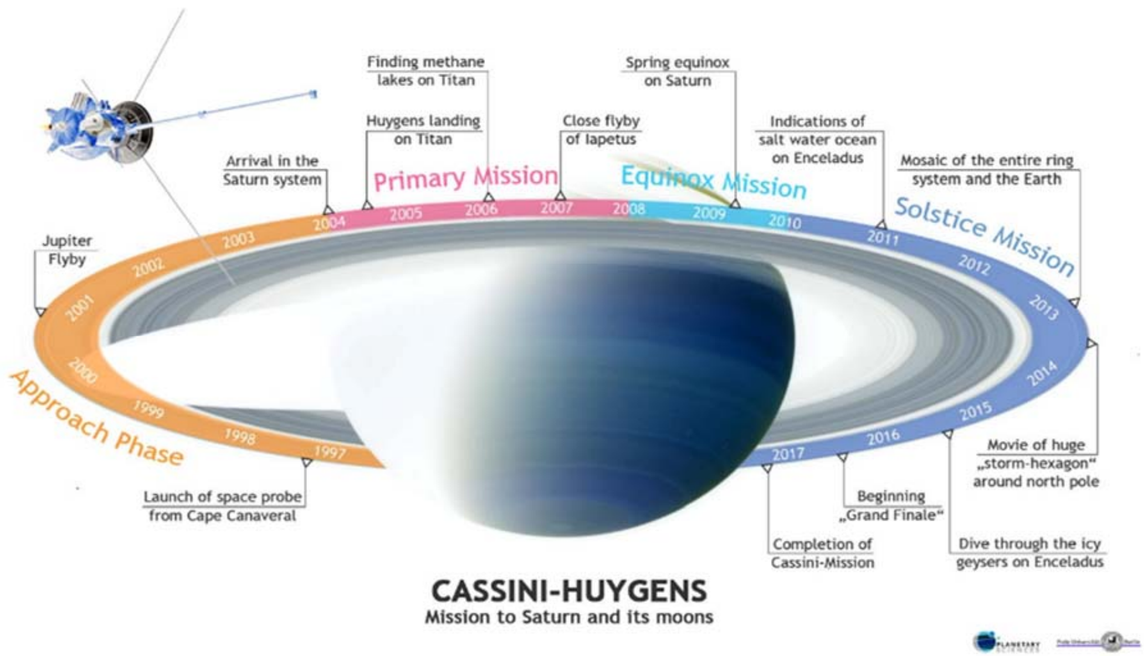

Figure 1: Cassini-Huygens project mission phases (Source: Freie Universitat Berlin)

The project (Cassini-Huygens) started on October 15, 1997, and ended on September 15, 2017. Cassini spacecraft inserted into Saturn orbit on July 1, 2004. About 13.5 years spent by the Cassini spacecraft orbiting Saturn allowed us to investigate this undisclosed planet's beauty. The mission was a collective enterprise of the European Space Agency, NASA, and the Italian Space Agency. The gathered dataset includes many images (453,048) taken by a narrow and wide-angle camera obtained by an instrument known as the Imaging Science Subsystem (ISS). Cassini has gathered samples and sending them back to Earth; returned samples confer experts to exploits up-to-date technologies to enlarge the scientific value. Among the gathered data, images are deemed the primary data source [6] (see Figure 1). The process of capturing images by the Cassini-Huygens venture wrapped up in the last part of 2017. The spacecraft of Cassini-Huygens included two components: the orbiter 'Cassini' and the Probe 'Huygens.' Cassini had the mission to capture and forward the data to the Earth. Huygens was destined to land on Titan, Saturn's largest moon, and forward Cassini's information. The image data set files were generated by NASA and made publicly

They offer limited event description, temporal/spatial approach, deficiency of knowledge representation techniques, and lack of an integrated approach to knowledge-based event processing. In our investigation research, we are interested in data volumes 1-116 containing the Cassini motion approach, insertion phase to Saturn orbit, up to the mission termination. The remainder of the paper is arranged in the following order: Section 2 presents the dataset utilized in the research analysis. Then we provide a concise outline of the related work. Next, in section 4, CKE Model architecture with related analysis and discussion is provided. CKE Analysis of the interplanetary data explained in section 5. Conclusions are addressed in section 6.

The previously mentioned points have motivated us to propose our continuous work approach to promote our intelligent framework regarding unsupervised anomaly detection schemes to seize these outliers. Whether they were extreme, special, or complex events, CKE's provided approach includes the era and transformation of theoretical perception and acknowledgment system integration with a complex constructive model

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connecting with the scope of coordinating mental schemas.

This adaptable strategy gifts the right set of circumstances to come over a gigantic expansion of strategies up to capable enforcement. It is hypothesized that Constructive Knowledge-based Event (CKE)algorithms find optimal solutions with less computational effort than optimization algorithms, iterative methods, or simple heuristics. For the up-to-the-model, a threshold value should be established to perform in a polynomial time and ensure convergence to the optimal solution.

2. DATA UTILIZED IN THE ANALYSIS

Cassini–Huygens spacecraft was so far the most aspirant expedition up till now sent to outer space, stuffed with a group of robust devices and cameras. Cassini-Huygens were eligible for gathering delicate measurements itemized images within several atmospheric circumstances. The spacecraft had two parts: the Huygens probe and Cassini orbiter, Cassini-Huygens arrive at Saturn in 2004, transmitting precious data back to us, which improved our comprehension of Saturn and its moons. Huygens step inside Titan's atmosphere, Saturn's massive moon, fall through a parachute to the furthest point so far, land on its surface, take samples, analyze them, and send the results Cassini, which will send them later to the Earth. Cassini instruments of remote sensing collected data remotely from enormous distances. After twenty years spent in outer space and thirteen years touring Saturn, the orbiter "Cassini" drained out of energy. Cassini was immersed in Saturn's atmosphere on September 15, 2017, and this is how the mission ended. The acquired image data has been generated by the Imaging Science Subsystem (ISS), which has the best resolution for the acquired images. The ISS is composed of 2 detached cameras wide-angle camera and a narrow-angle camera. ISS image volumes dataset is composed of many images and their related labels that hold the images' metadata. The data set is publicly available at the following URL:https://pdsimaging.jpl.nasa.gov/volumes/iss.html [7].

3. RELATED WORK AND PREVIOUS STUDIES

The related work on complex event detection and processing is briefly reviewed in this section. Remarkable efforts have been dedicated to the aim of detecting complex events and conducting reasoning. Models of this kind are as often as possible carried out as a generation system with a flexible implies that allow the capacity to come over a broad span of plans up to capable accomplishment indeed with complex errands. Schoppek offered a rigorous reasoning model that was qualified to assess and direct a minor dynamic system via reliably relying on linear system equations [8]. The demonstration contained a clear cerebral outline of the technical system and thought procedures to secure input values. The embraced method is satisfactorily comprehensive to organize any simple framework.

Consequent considers how these frameworks' approaches may be extended to generalization execution inside complex real essential timing correlation that incorporates choice-forming, such as controlling the functioning of a jet plane [9]. In planning the errands of actual-time dominion, the noteworthiness ordinarily counts on mimicking the time way of monitoring preparation. Traditional mistakes [10] presented an event scoring algorithm to detect evolution correlations. This algorithm exploits the timestamp, temporal contiguity, content resemblance to display the event evolution interconnections. A plan-based approach [11] proposed a plan-based method for exchanging information related to complex event detection over distributed sources, providing a cost-based multi-step identification scheme depending on the temporal constraints and event frequency statistics ingredient events.

J. Yang et al., the authors made an imperative stride concerning suggesting a CEP by counting on reasoning principles and the scope of computing, in the role of that they overviewed the extant methods among three aspects included in semantic, iterative, and intelligently [12]. Storrs, K.R., and Kriegeskorte, N. have tried reasoning speculations by utilizing profound learning instruments to assess its helpful and incipient behaviors. In arrange to utilize profound learning to enlarge the prepared speculation show to be qualified to perform complex errands. The authors in [13] introduce pertinent schemas and techniques used in reasoning modeling, reasoning with good sense, and sound judgment in practical matters. Moreover, defiance and significant questions of other research are presented, e.g., developing a complex computational paradigm that can be a contestant with humans' reasoning on trouble that needs prevalent sense or significance. In the role of researchers in [14], they illustrate the leverage of integrating reasoning with machine learning and neural-symbolic computing via delineating the major

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features of the schema and representing the reasoning that allowing building an interpretable AI framework which could lead the way for the growingly eminent necessity for the explainable and trustworthy system.

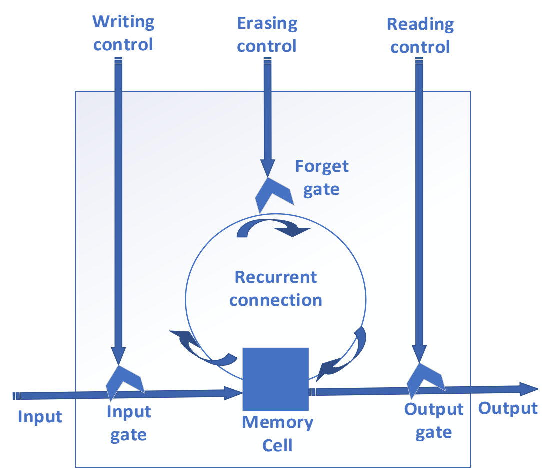
The work of [15] addressed the major challenges within the field of machine learning and reasoning products and provide stimulations for additional development, especially in the scope of empowering reasoning competence, just like cognition and perception, which could lead to additional dependability, robustness, and enhanced performance, their work suggests a top-level reasoning schema, that is targeting conceptual prototypes of reasoning scopes. [16] This paper presents a performance model and an ontology approach to discover or identify the presence of complex events for the actual time during which a process or event occurs in the system. These previously mentioned works have incurred and stimulated us to utilize the intelligent mechanism via stacked bidirectional LSTM network layers to identify a constructive knowledge-based event.

4. AMALGAMATING OF DEEP LEARNING ALONGSIDE CKE

Objects detection has always procured a significant volume of attention from analysts and researchers since Deep Neural Network Systems (DNNs) have been competent for accomplishing in the vicinity of human-level rendering [17]. Exploiting (DNNs) inside a constructive scheme contains a centrality that permits clamor reluctance and present error recovery. Moreover, these networks are qualified to memorize the input modality or structure that does not require earlier information. CKE distinguishing proof demonstrates slants for both consolidation and constancy for the classification process.

Developed three decades ago, multilayer Recurrent Neural Networks (RNNs) have the lion's share of frequently utilized deep learning methods [18]. These kinds of neural networks possess a memory that registers the data that they have dealt with before. Furthermore, RNN is a robust method for handling sequential data [19], and they utilize the former output to predict the following output. In such circumstances, the RNNs have recurrent loops. Those loops are among the hidden neurons, which permits keeping the former input data for a period. As a result, the model gains the ability to predict the forthcoming output. The output generated by the hidden layer is resent (τ) times toward the hidden layer.

The neuron's recursive outcome is forwarded to the subsequent layer whenever the cycle of iterations is accomplished. With the current status, the output is more inclusive, and the former information is preserved for a prolonged period. Eventually, the errors will be sent inversely to bring up to date weights. To treat the prominent temporal overreliance, the RNN is a logical option concerning the net-work recurrent connections, which let the network recall memories of former inputs [20]. Nevertheless, typical RNN does not possess the tendency to impart on-term time overreliance due to the gradient vanishing dilemma. LSTM can overcome this issue by put to use the featured memory cells structure. Via stacking memory cells, previous data inputs could be stored in the output to a certain extent, conveyed by cell state. Figure 2. Represents a notational LSTM layout.



Figurer 2: LSTM layout (notional)

4.1. CKE Analysis System Architecture

It should be mentioned that this research is a resumption of past investigation exertion associated with the Cassini-Huygens project dataset [19, 21, 22]. CEP and discovery is an extravagant ponder space escorted with numerous limits to be hypothesized, the profiteering of learning approaches to arrange and uncover uncommon events proffer a gigantic tolerable to be utilized on another external space voyages, due to the colossal mileage space between the Earth terminal and the shuttle that requires vital time, which suggests that the reaction to any occasion might not be carried out amid the requisite period of time [22]. One of the significant ponders discourse around constructive modeling concerning if the computer can perform

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insights modeling as the human does. Intellectuals customarily show to the limitations on what may be considered computable indeed come to proposing that human insights might not be computational. Figure 3. shows the pattern classification procedure.

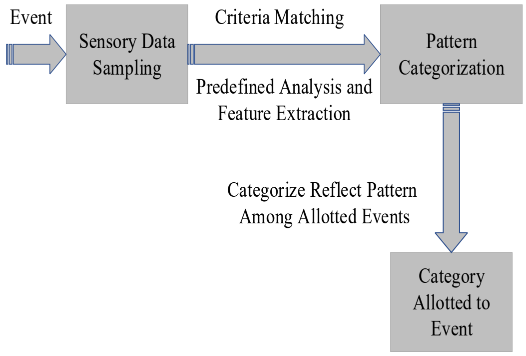

Figure 3: Classification of sampled patterns

There are hypothetical results from information preparation and computational concepts that have had a colossal impact on constructive modeling.

The broadscale point in pattern classification is to postulate the denomination of a method and to construe the detected information to the demonstrated design for the suggested model of CKE appears in (Figure 4).

The framework secures the information and stats with the method of analyzing this information and recognizes the event within the data at that point, an additional assessment, and preparing to distinguish the uncommon (special) events among these occasions. The model presents the concept of splitting the available dataset into two primary (representative, large enough) subsets: training set which is a subset that is exploited for model training. While the test set is a subset that is utilized for model testing.

Within machine learning, the significance of model validation can be indicated as an approach at which the trained model will be evaluated through the dataset of testing. The data set of testing is an autonomous part of the original dataset that includes the training portion. The principal aim of carrying

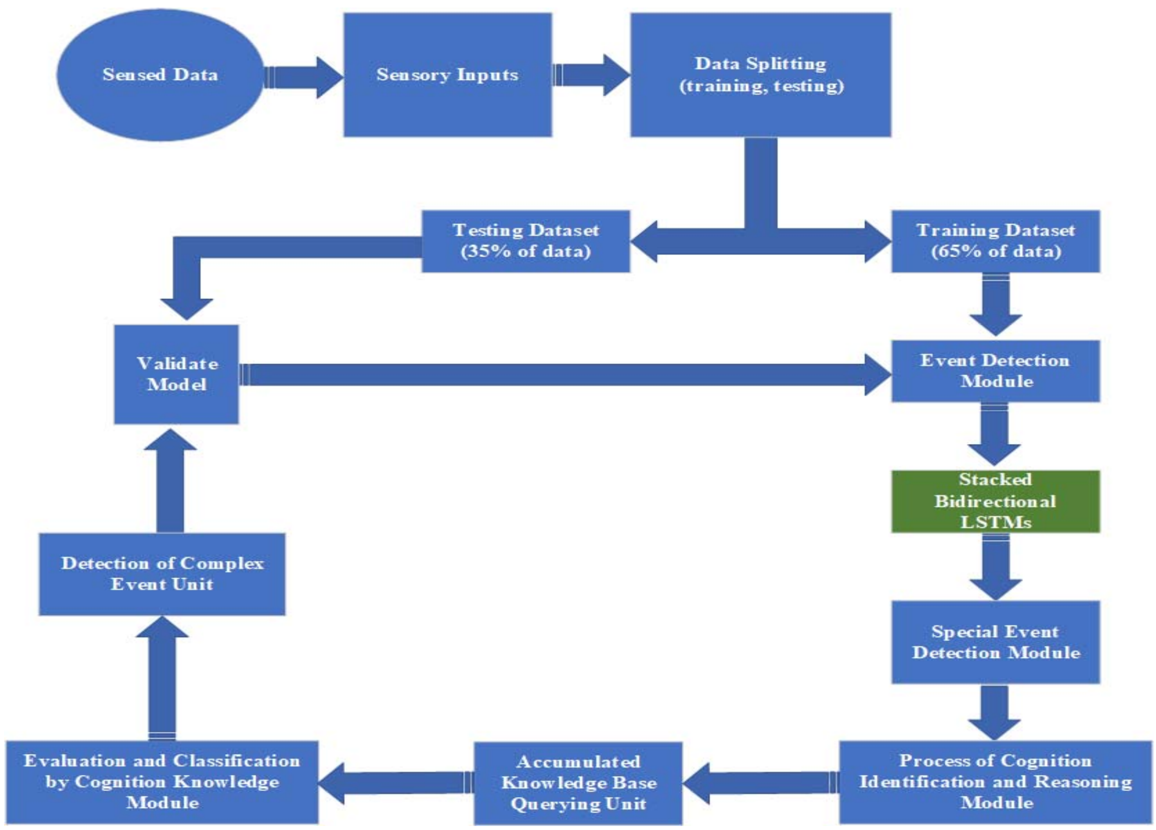

Figure 4: The architecture modeling process of CKE

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out the testing process is to examine the trained model generalization competence [22].

Deep learning for that cause is pertinent to any individual who is attentive to recognition and knowledge protrude from neural vitality. Our approach function starts to undertake the mode of perception reasoning afterward, the framework keeps the outcome in its learning repository for the following reasoning phases, the subsequent phase of the model includes heading to the constructive categorization stage, and its task is to appoint the complex events depending on this reasoning process of categorization. A detailed illustration of the proposed approach is given below:

1. Sensory inputs: sensors for planetary data that contain measurement and readings making up huge sensory data, including delineating from an autonomous modality depiction that will go through the event detection process among the observed data, overlook clamor in arrange to attain the specified match of demonstrating complexity. These sensory data are required to fulfill our perception and maximize the utilization of the valuable gathered data. We provide a model of artificial intelligence using this sensed data to allocate events and detect special events. Then this data enters a process of cognition and classification to detect complex events.

2. Event Detection Module: the provided event detection module extraordinarily complies with the pipeline processing in steps. To determine the complex event for many-scale categorization, we make practical and effective use of stacked bidirectional LSTM. The method assumes that autonomous input is not only a one-dimensional vector. Also, it could be multidimensional tensors likewise. To integrate such objects, we are utilizing tensor normalization. The growing computational potentials and GPU programming prevalence latterly made deep learning models inordinately rife, with implementations that range over data mining, image processing, and complexity analyses.

Bidirectional RNNs were initiated to deal with the situation at which the prediction relies on both the past and subsequent elements. In the actual application or use of an idea, the bidirectional RNN amalgamates [23]: The first layer of RNN that goes in a specified direction forward over time and commences from the sequence onset and a second RNN, which is made up of exactly similar parts, symmetrical with a backward movement over time and starts from the sequence end. While the output (b) at step t includes the output 'forward RNN,' which starts from the sequence onset and goes in a forward direction over time, the other begins from the last part of the RNN sequence and goes in a backward direction over time. Figure 5. shows the organization of an exemplary bidirectional RNN [24].

3. Special Event Detection Module: such detection in a vast data set is often possible advance for information examination and elucidation than just an explicitly stated modality, particularly within the technique of multivariate investigation time arrangement, within the situation of a deviation among the conventional disposal is recognized. A special event could be characterized depending on the limit (max-limit), followed by many labels that identify particular modalities such as receiving start and stop time, temperature, and packet receiving rate.

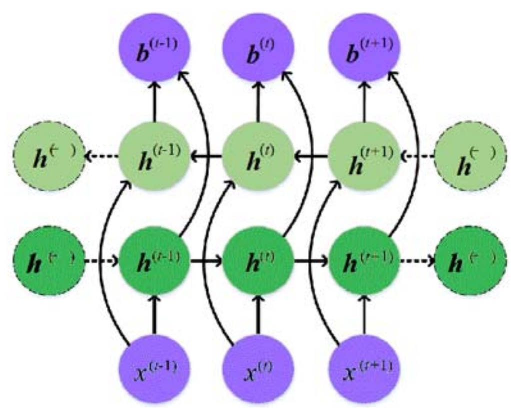

Figure 5: Bidirectional RNN structure

4. Process of Cognition Identification and Reasoning Module: cognition is an intellectual handle of doing something regularly to attain a point of getting information through thought, observation or experience (an occurrence or event), and detecting. It joins various particular properties of mental occupation, thinking, reasoning, and assessment. Constructive reasoning and recognizable proof include modality distinguishing event components, incorporating its qualities and information sorts such as perceptions and modality observations. This module utilizes existing facts, information, and recognition to produce not existing before(unprecedented) knowledge.

5. Accumulated Knowledge Base Querying unit: the previous knowledge-based approach of constructive dialectics usually pays attention to the classification viewpoint because of the tremendous extent of the dataset. This unit creates a preparing series from the former generated information. The

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querying unit process incorporates the method of query and reminiscence, which is assigned to the stacked bidirectional LSTM. In arrange to obtain improved execution by settling the associated matters to the inquiry by collecting various outcomes-sets created from past inquiries.

6. Evaluation and Classification by Cognition Knowledge Module: the module of classification needs a precise merits extraction to extricate intricate merits. The classification process is predominant within the space of data frameworks. Classification reduces the complexity of executing among individual module parts as a replacement of being have to recall each merit of every component. Classification reduces the complexity of executing among individual module parts as a replacement of being have to recall each merit of every component.

7. Detection of Complex Event Unit: a complex event is made by analyzing extraordinary (special events) by utilizing many parameters. Like the level of the identified changes within the modality, as each extraordinary event is associated with all intervals of times that mention its occurrence span term. Concerning special events, the related time interval is considered a measure that gives the starting and wrapping up the point of the uncommon event. Whereas with complex events, the apportioned time intervals contain the duration or the parcels of time of the full sub-events. These cognitive intervals are ideal for gathering the fundamental extraordinary (special events).

4.2. CKE Model Analysis and Discussion

More often than not, features such as edge or lines are considered as a primary descriptor that can be easily indicated without executing any complex procedures, which is recognized as (bottom-level) or common features that are generally designated to those nonexclusive features which may be directly observed from any displayed image, such as surface or line merit. Lineaments which are categorized as a high-level indicate the features vectors that are gotten from bottom-level merits via utilizing affirmed advanced approaches. Fig. 4 provides a proposed filtering model for detecting a complex event. This algorithm identifies special events of the multivariate time series. We constituted the event detection process as following, let

$$\Omega = \{\mathrm{v}_1, \mathrm{v}_2, \dots, \mathrm{v}_\mathrm{k}, \mathrm{t}\} \quad (1)$$

be the space of events, where $v_i, i = 1, \dots, k$ are k independent variables, and t represents the time. Accordingly, we inspect discrete points in time (moments) of the process of sampling, denoting variable t to be classed to the finite time set S:

$$S = \{0 = t[0] < t[1] < \dots < t[n-1] = T\}, \quad (2)$$

where $n \epsilon \mathbb{N}^*$. We defined the time interval among the analyzed dataset with a distinct measure such that $\Delta t = \Delta t[m, r]$, and

$$\Delta t = [t[m - \lfloor r/2 \rfloor], t[m + \lfloor r/2 \rfloor]] \subset [0, T], \quad (3)$$

where $m, r \epsilon \mathbb{N}^*$ are middle index and number of samples in the underlying time interval, respectively. Parameter r is used as the memory size of the CKE model. The number of outliers $O_i[m, r]$ for variable v_i in time moment $t[m]$ and memory size r is the cardinality of the set $V_i[m, r]$ given by the formula below:

$$V_i[m, r] = \{v_i[j] \mid \frac{\left| (v_i[j] - \overline{v_i[m,r]} \right|}{\sigma_i[m,r]} \geq \rho\}, \quad (4)$$

where $\overline{v_i[m, r]}$ and $\sigma_i[m, r]$ are moving average and local standard deviation of the variable v_i, respectively in time interval $\Delta t[m, r]$ and $j = m - \left\lfloor \frac{r}{2} \right\rfloor, \dots, m + \left\lfloor \frac{r}{2} \right\rfloor$. ρ represents the outlier detector sensitivity, and it is specified via the acquisition of knowledge (learning process). The outlier searching method in formula (3) uses the absolute standardized time series of variable v_i for each time interval $\Delta t[m, r]$. Severity function $f_{CKE}[m, r]$ of the space Ω in time moment $t[m]$ and memory size r are given by:

$$f_{CKE}[m, r] = 1 - \frac{1}{k} \sum_{i=0}^{k-1} \frac{O_i[m,r]}{r} \quad (5)$$

Values of severity function $f_{CKE}[m, r]$ belong to [0,1] as in time interval $\Delta t[m, r]$ every variable owns at most r outliers. In that respect, there are k independent variables utilized in equation (4). The subset $S_{CKE} \subset S$ is named CKE set of space Ω and is given by the following formula:

$$S_{CKE} = \{t[m] \mid Th < f_{CKE}[m, r] < 1\}, \quad (6)$$

where Th is the severity threshold determined by the learning process and $m = 0, \dots, n$. Because of the positive and subunit range property of severity function mentioned before possible range for the severity threshold Th is $(0, 1]$. The higher is the Th, the stronger becomes the severity of the CKE method, and the lower number of events are identified as special events. Learning phase execution is required to determine the optimum values of parameters r, ρ, and Th before applying in practice this CKE analysis

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method. The hitting rate of the CKE method is the ratio of found SEP events (cardinality of S_{CKE}) and the total number of samples (n). The presented approach handout eminent results, we found that there is a need for an approach that guarantees knowledge representation with precis event reasoning. The event's definition through logic and reasoning is addressed with our approach. In addition, it relies on and implements knowledge-based event intelligent identification.

5. CKE ANALYSIS OF THE INTERPLANETARY DATA

The used dataset is downloaded from NASA's jet propulsion laboratory. We are concerned with the data captured during the period that extends between [16-Feb-2004, 15-Sep-2017], which is almost 13.5 years, where the dataset sample n = 407,303. We are interested in these samples as they represent the acquired data after Cassini's spacecraft was inserted into Saturn orbit. Data collecting was carried out within various phases as well as sub-phases across the outer space mission. Every sub-phase also contains many sequences to which every sequence involves a specific figure or quantity of observations based on the judgment of the Cassini imaging team mission and other related teams such as engineering. The observation includes a series of samplings at which the size of the set counts on scientific events of the orbiter Cassini or outer space events related to the followed path.

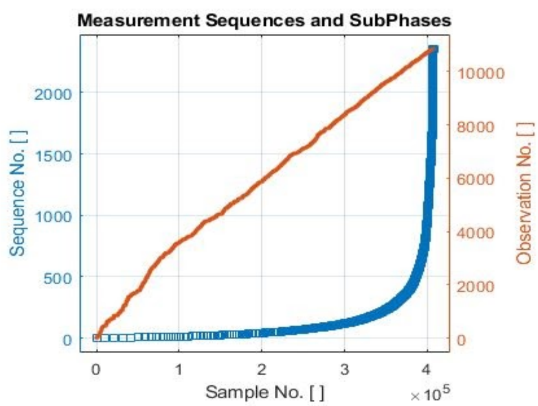

Figure 6: Measurements of sequences and subphase vs. sample number

In addition to the number of observations in the inspected time interval, the sequences were 2,355 and M = 10,850, respectively. Potential complex events of the data set are in the moment of change of observation sequences. Figure 6 shows sample ID vs. the number of observation and sequences, where the subphases number have an exponential graph, while the number of observations has linear time dependence.

Within the conducted examination, we utilized small proportional quantity but representative group of independent variables ($k = 8$, see Table 1). The supervised learning process for specifying the CKE technique's operating values for memory size r, the sensitivity of the outlier detection method ρ, and severity threshold Th of the method we used first 1% subset of the total samples ($n_{learn} = 407{,}3$). The remainder of 99% of the data were utilized as test data to validate the CKE analysis model. Sampling intervals and sampling durations are given in Figure 7 and Figure 8, respectively.

Table 1: The analysed list of independent variables

Var.	Variable Name	Description
v_1	Sampling interval [s]	Time int. between consecutive samplings
v_2	Sampling durations [s]	Duration of samplings
v_3	Detector temperature [°C]	Temp. of Charged Coupled Device (CCD)
v_4	Filter temperature [°C]	Temperature of Wheels Filters
v_5	Diff. No. of packets/image	Abs (expected – received) packets/image
v_6	Data Transmission Rate [kbit/s]	Rate of transmitted data by the orbiter
v_7	Image compression ratio [bit/pixel]	Received images compression ratio
v_8	Picture exposure time [s]	Exposure time of picture

Sampling interval and sampling duration will satisfy the time domain necessity.

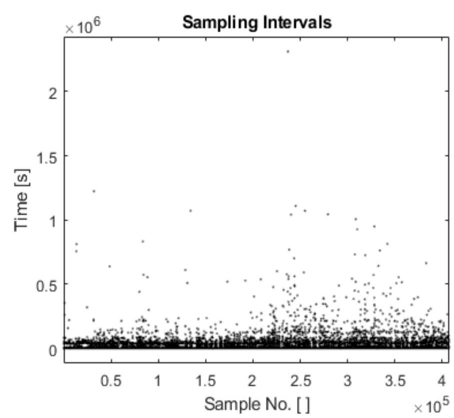

Figure 7: Sampling intervals at the Cassini orbiter

The horizontal axis shows the sample number, and the vertical axis represents the time. The sampling time shows the time interval among consecutive samples, while the sampling duration means the difference in time among two successive samples.

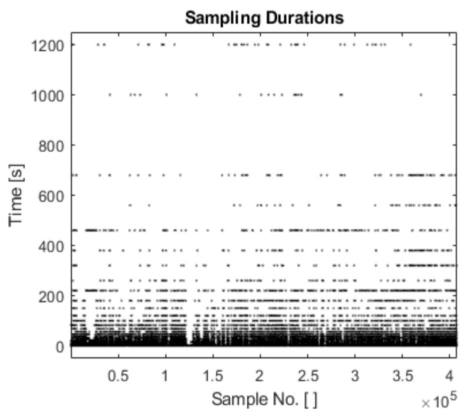

Figure 8: Sampling durations at the Cassini orbiter

Under the varied ranges of the temperature for the detector and the filter, it is possible to detect special events by detecting the set of discrete points in the represented data.

By utilizing deep learning, we are training our model to learn the implicit pattern and rules spontaneously. Once the model is trained, we could introduce new data to detect complex events through a black box with an output function based on our proposed model. The investigated detector and filter temperature are represented within (Figure 9 and Figure 10).

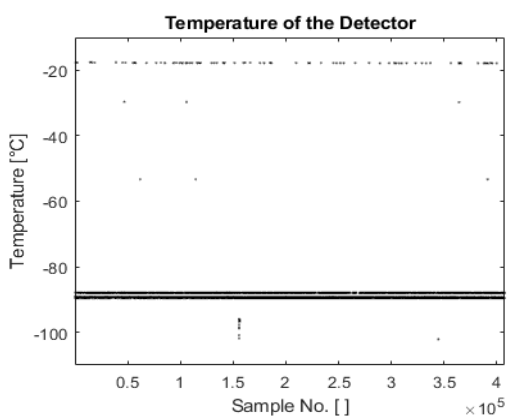

Figure 9: Detector temperature of Cassini orbiter

The proposed model is arranged to vouch that each event observation among the sampling interval will be checked. It can be noticed that the indispensable sampling time is around 15 s or more. The temperature of the detector and the filter is working in very different ranges. It is noticed that the data transmission rate is varied based on the active phase of the mission as the transfer rate ranges between 5 kilobits per second at the minimum rate, while the maximum rate is 365 kilobits per second.

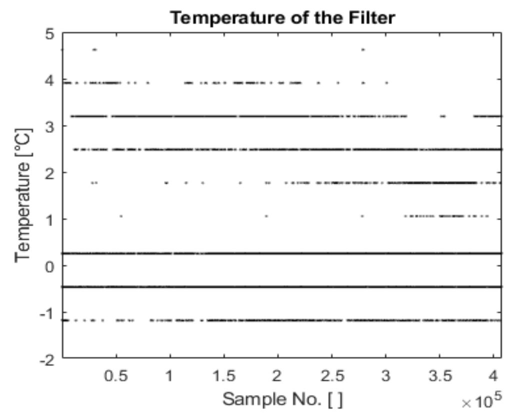

Figure 10: Filter temperature of Cassini orbiter

The time dependence of the error rate and the transfer rate are given in Figure 11 and Figure 12, respectively. The model provides the ability to track several observations.

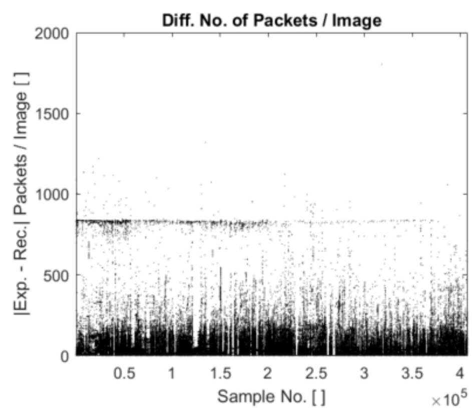

Figure 11: Difference No. of packets/image

In practice, the expected packets and received packets for each image are different because of the image sampling quality.

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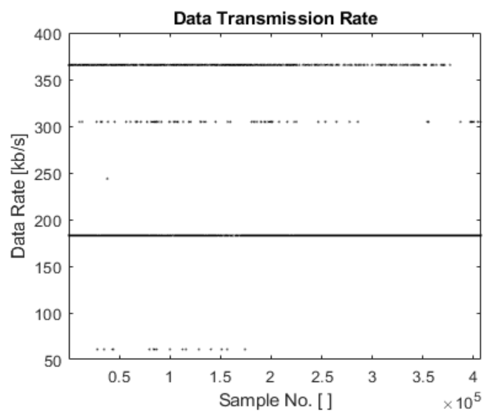

Figure 12: Data transmission rate by Cassini

Radio signals shall need between 68 to 84 minutes to make its journey across the space separating Cassini and the ground station on the Earth. The data transmission rate is varied based on the active phase of the mission as the transfer rate ranges between 5 kilobits per second at the minimum rate, while the maximum rate is 365 kilobits per second. The content influences picture exposure time and compression of sampled data at the Cassini orbiter (see Figure 13 and Figure 14). Through the analysis, it is also expected that there will be several picture exposure times ranging from 0-1200 seconds. Short exposures are used needed to reduce smears throughout close Cassini flybys.

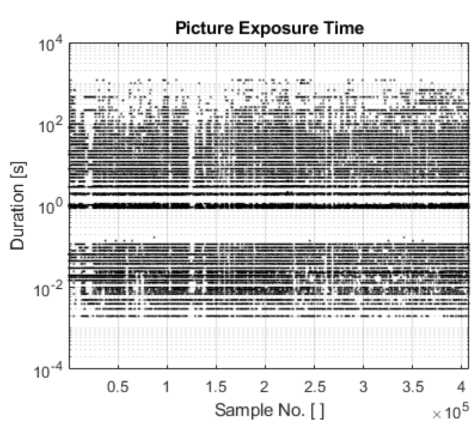

Figure 13: Picture exposure time at Cassini orbiter

The compression ratio extent between 2 and 3 is determined by the data actual entropy. Moreover, based on the running activity, it incorporates different ratios ranging from 2:1 to the ratio of 10:1.

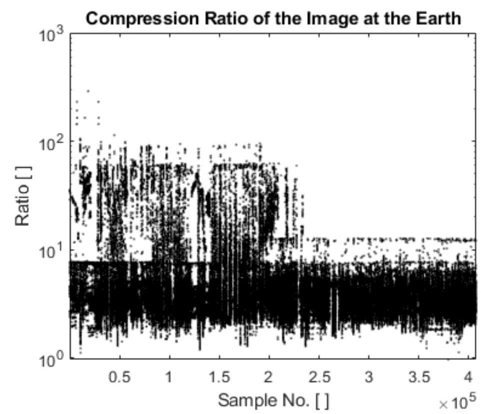

Figure 14 Compression ratio of the received images

Our artificial intelligence model qualified us to detect and confirm a considerable number of complex events based on these variations of ratios. The dependence of the CKE method hit ratio on parameters r and ρ are given in Figure 15, while the detected special events via the proposed method are presented in Figure 16.

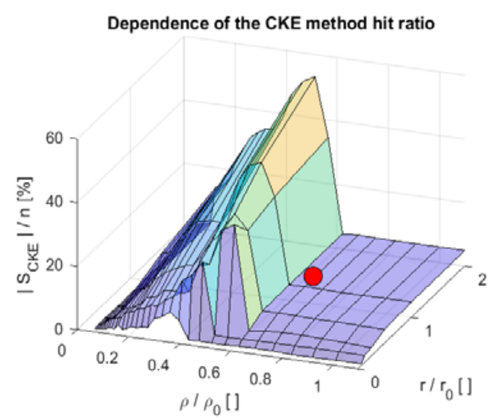

Figure 15: Dependence of the CKE hit ratio on r and ρ

For the learning time series of the C-H project, it was found that the optimum memory size is $r^* = 1 \cdot r_0 = 2$ and the optimum sensitivity of the outlier detector is $\rho^* = 0.7 \cdot \rho_0 = 0.7 \cdot (\max(V) - \min(V))/\,\sigma[n,r]$. The optimum severity threshold Th of the CKE method was determined based on the requirement to find the nearest number of special events to the number of sequences $(M = 10{,}850)$ executed during the project.

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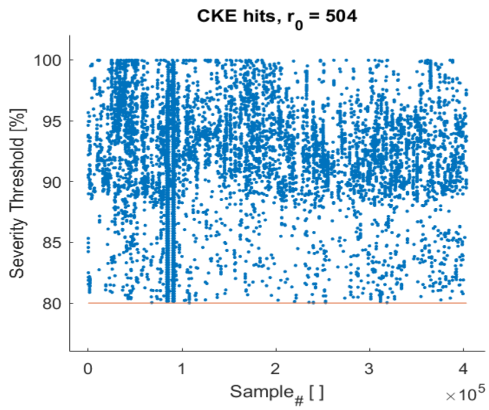

Figure 16: Detected special events by CKE method

The memory size and severity threshold were found to be $r^* = 504$ and $Th = 87.6\,\%$, respectively. Resulting in $|\,S_{CKE}\,| = 10{,}134$ number of special events detected in the testing data inducing hit ratio of the special events to be $|\,S_{CKE}\,|\,/\,n = 2.4\,\%$.

6. DIFFERENCE FROM PREVIOUS WORK

In reality, a comprehensive personal screening of all papers in a collection of sources may be more successful but much more time-consuming. However, there is such a powerful temptation to discriminate by inventing our own algorithm in a certain well-defined theme; there could be hundreds of various ways or methods to designate a similar methodology. CEP's main characteristics are scalability, performance, timeliness, robustness; this is what we proved by the acquired outcome and confirmed hypothesis. It inputs limitless, infinite events stream from the sensory data source, and the proposed model is capable of filtering, aggregating, data inferring complex events within stream data. The suggested algorithm focuses on sensory data processing.

7. CONCLUSIONS

This research paper presented a novel method to detect special events of a complex process based on the Constructive Knowledge Identification method. Inside this investigation work, we provide a model to analyze the time-related multivariable flow of events and demonstrate to insert complex events recognizable proof with constructive reasoning vis utilizing stacked bidirectional LSTM networks. Based on the learning subset, the self-evident utility of CKE recognizable proof shows that just 93.4 % of the sequence changes executed during the Cassini-Huygens project generated special events. This phenomenon is caused by the high number of relatively short and similar sequences performed in the project's last months. More evaluations are planned to identify and explain the CKE method's dependence on the distribution in time of the special events. The proposed model shows immense promise for intelligent identification techniques, as it expedited and simplifies the dynamic analysis of the big data within a reasonable short time.

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