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SCIENTIFIC CULTURE, Vol. 12, No. 2.1, (2026), pp. 13916-13925
Open Access. Online & Print

DOI: 10.5281/zenodo.20488930

AUTOMATING ASTROLOGICAL INFERENCE THROUGH RULE BASED DECISION SYSTEM FOR MUHURTAM STRENGTH EVALUATION

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Received: 04/04/2026
Accepted: 20/05/2026

ABSTRACT

In the current era of data-driven decision-making, the intersection of traditional domains like astrology and Automated Decision Systems (ADS) reains largely unexplored, often due to a perceived lack of algorithmic rigor and standardized empirical frameworks. Unlike established scientific fields, traditional astrology has historically lacked the formalized logic and rule-based architectures necessary for seamless integration into modern Machine Intelligence pipelines. This research introduces a high-fidelity inference engine designed to transform qualitative astrological reasoning into a structured, computational framework. By leveraging a specialized algorithm, we successfully automated the extraction of logic-based decision rules to evaluate the "Muhurtam strength" for marriage—a complex multivariate optimization problem. The system functions as a feature-processing pipeline, ingestioning high-dimensional inputs including:

- ***Celestial Geometry: Planetary coordinates within the natal and horary charts.***
- ***Temporal Metadata: Multi-layered data extracted from traditional almanacs.***
- ***Relational Features: Analysis of the Lagna (ascendant) and diurnal variables (day of the week).***

These disparate data points are synthesized through a quantitative scoring model to determine the objective strength of a specific time window. To ensure model reliability, the system was validated against a structured dataset; using a standard train-test split methodology, the architecture achieved a predictive accuracy of approximately 70%. This study represents a significant leap in the computational formalization of esoteric knowledge, providing a scalable foundation for merging ancient heuristic systems with the next generation of AI-driven decision-support technologies.

Keywords: *Inference rules, Automated Decision System, Muhurtam, Astrological facts*

2. INTRODUCTION

Historically, astrology has been categorized as a heuristic-based belief system rather than an empirically grounded discipline, primarily due to the absence of **externally validated logic frameworks** and **standardized scientific protocols**. While legacy software has long automated astrological calculations, these tools typically function as "black boxes," lacking the **explainability** and **algorithmic transparency** required to provide scientifically reasoned interpretations. However, contemporary research is increasingly focused on the **computational formalization** of this domain through the integration of **empirical data pipelines** and **rigorous scientific methodologies**.

In today's media-saturated landscape, digital platforms have significantly amplified the visibility of astrological practices. Yet, even when expert practitioners provide predictive insights, the underlying **feature-logic** remains largely opaque to the end-user, lacking a **scientifically coherent justification**.

To bridge this disconnect, **Artificial Intelligence (AI)** offers a robust framework for the **structural encoding** of astrological knowledge. By emulating human cognitive reasoning and complex decision-making, AI facilitates the development of **Automated Decision Systems (ADS)**. The architecture of such systems necessitates a high-dimensional **training phase** utilizing diverse real-world datasets, followed by **rigorous cross-validation**. This involves an **iterative optimization loop**—where the model is continuously retrained on emergent data scenarios until it reaches **convergence** and achieves **statistical stability**. Maximizing **predictive accuracy** remains the primary objective of this AI-centric development.

This study details the construction of a specialized dataset, subjected to **exploratory data analysis** to identify critical **input parameters** and **target variables**. From this, a set of **inference rules** was synthesized to automate predictive outcomes. These rules were developed as a **language-agnostic logic layer**, ensuring interoperability and portability across various computational environments.

Following standard **Machine Learning (ML)** protocols, the dataset was partitioned into mutually exclusive **training and testing subsets** to evaluate **generalization performance**. Central to the methodology is the integration of **Case-Based Reasoning (CBR)**, deployed through three modular components designed to derive **automated, scientifically grounded heuristics**. A **classifier model** was subsequently trained and benchmarked, with performance metrics focused on minimizing **mean deviation** and maximizing **classification accuracy**.

Finally, **Data Visualization** is leveraged as a core component of the ADS architecture. By transforming complex model outputs into intuitive graphical representations, we enhance **model interpretability** (XAI) and provide visual verification of the system's **predictive validity**.

3. LITERATURE REVIEW

Gabriel Terna Ayem, Salu George Thandekkattu, and Augustine Shey Nsang presented a comprehensive review on causal identification techniques across diverse and unconventional data settings, addressing a notable gap in the existing literature. Their work offers a structured classification of standard algorithms used to infer causal relationships within datasets, categorizing them into three primary models: constraint-based, score-based, and functional-based approaches. The authors further explored various causal discovery models applicable to ten distinct data settings, which include: Linear Non-Gaussian models, Non-Linear additive noise models, time-series causality challenges, deterministic data environments, heterogeneous and non-stationary data, missing data scenarios, measurement error issues, data selection bias, confounding and latent variable contexts, and datasets characterized by cycles or feedback loops **[1]**.

Kumari, R. and Lal, S. P. examined the significance of the Navagraha (nine celestial bodies) in relation to human well-being and environmental harmony. Their study, titled *Navagraha-Vatikaas*, highlights the association between nine specific plant species and their corresponding planetary influences. The term *Vatika*, denoting a garden or green space, underscores the ecological dimension of the study. Notably, the authors observed that Navagraha-associated plants exhibit higher oxygen release compared to other species. Furthermore, the layout of Navagraha Vatikas adheres to geometric and systematic principles aimed at promoting environmental balance. The study also provides detailed guidelines on the establishment and management of such gardens, including site selection, soil and climate requirements, infrastructure, and design considerations **[2]**.

Zador, A., Escola, S., Richards, B., and colleagues proposed a novel trajectory for advancing artificial intelligence through foundational research in NeuroAI. Their work introduces the concept of the "embodied Turing test," which challenges AI systems to emulate animal-like interactions with the sensorimotor world across varying levels of complexity. The study emphasizes three critical dimensions for progress in this domain: environmental interaction, behavioral flexibility, and computational efficiency **[3]**.

Schultheis, A., Zeyen, C., and Bergmann, R. addressed the challenge of selecting an appropriate Case-Based Reasoning (CBR) framework tailored to specific application requirements. Their comparative analysis evaluates five recent open-source CBR frameworks based on criteria such as CBR types, knowledge containers, process phases, user interfaces, and unique features **[4]**.

McRitchie and Kenneth Douglas contributed to the field of astrological research by outlining a three-stage modeling approach to address design limitations. These stages—Single-factor, Multi-factor, and Chart-matching tests—were used to evaluate astrological hypotheses. The chart-matching stage, in particular, yielded substantial effect sizes. Their study also juxtaposed astrological inferences with philosophical constructs from other disciplines, focusing on measurable processes and emergent outcomes **[5]**.

Corey Cusimano and Tania Lombrozo explored the cognitive dimensions of motivated reasoning, particularly in domains where individuals exhibit minimal awareness of their biases. They argue that in the absence of empirical evidence, individuals often regard their beliefs as morally justified, leading to a form of desirable motivated reasoning. This phenomenon, they suggest, challenges traditional assumptions about naïve realism and cognitive blind spots. Their findings highlight how self-awareness and ideological pride can both hinder and enhance reasoning, offering new avenues for addressing ideological polarization **[6]**.
I. K. Nti, J. A. Quarcoo, J. Aning, and G. K. Fosu conducted a review of the most widely adopted Big Data Analytics tools, focusing on their application in economic domains. Their study synthesizes prior research on the integration of machine learning techniques in big data analysis across various economic sectors **[7]**.

Ozan Okudan, Cenk Budayan, and Irem Dikmen developed a knowledge-based system named **CBRisk** to address risk management challenges in construction projects. This web-based tool employs Case-Based Reasoning (CBR) and integrates fuzzy linguistic variables to enhance the effectiveness of case retrieval in the risk management (RM) process. The tool was rigorously evaluated through black-box testing and expert review sessions to validate its functionality and practical applicability **[8]**.

Sharma and Sri Prathyangira Swamy explored the astrological underpinnings of diabetes by analyzing horoscope charts. According to their findings, the sixth, eighth, and twelfth houses, along with the planetary influences of the Moon, Jupiter, Venus, and Saturn, are associated with the onset of diabetes. The study presents both diagnostic insights and remedial measures grounded in astrological principles. The authors formulated a set of astrological rules for identifying diabetes and illustrated them using *Lagna*-wise *Navamsa* and *Rasi Chakra* charts **[9]**.

Fatemeh Dehghan and Farzad Kiani investigated the influence of social networks on lifestyle changes during the COVID-19 pandemic. Their descriptive study analyzed qualitative Twitter data collected over two months, segmented into two phases. Approximately 100,000 tweets were gathered from four user categories: private individuals, government officials, celebrities, and healthcare professionals. Sentiment analysis was conducted using a Support Vector Machine (SVM) model, which achieved an accuracy of nearly 97% and an F1 score of 92%. The findings indicate that social media contributed to approximately 30% of lifestyle changes and stress during the pandemic. The authors emphasized the critical role of disseminating accurate information through trusted channels for effective societal governance **[10]**.

Samaranayake G. V. P., Dharmapriya A. K. H., and Ven. Dhammissara Maduruoye conducted a study in the domain of Medical Astrology, examining the correlation between planetary positions and human diseases through the lens of zodiac signs. Their research highlights the *Kalpurusha* framework, wherein each zodiac sign corresponds to specific body parts, beginning with Aries. The study posits that astrologers can predict disease susceptibility, onset, and duration based on planetary periods and sub-periods. The authors also explored the intersection of astrology and Ayurveda, emphasizing the diagnostic potential of astrological analysis **[11]**.

Hou, M. Han, and Z. Cai underscored the significance of big data in analyzing abnormal events and natural disasters. They categorized social media platforms into five content types: wikis, blogs, microblogs, opinion/review sites, and question-answer forums. The standard data pipeline for social media analytics includes stages of data collection, storage, analysis, and visualization. The authors discussed various analytical techniques, including topic modeling and sentiment analysis, to extract actionable insights from social media data across multiple sectors **[12]**.

Dimri and L. Kush presented a comprehensive review of astro-medical profiles associated with zodiac signs. Their study included two detailed tables: the first mapped zodiac signs to ruling planets, corresponding body organs, planetary victuals, and associated mineral salts; the second outlined the influence of planets on human physiology and their astrological associations with vitamins. The authors proposed a scientific basis for the astrological impact on human pathology, emphasizing the connection between planetary influences, minerals, and biological precursors **[13]**.

4. METHODOLOGY

The proposed **Automated Decision System (ADS)** evaluates the computational strength of a *Muhurtam* through a sequential, modular pipeline consisting of three primary **feature-processing engines**: lagnaStatus, rahitamStatus, and basic_computations.

The system ingests a high-dimensional **structured dataset** containing temporal and celestial **features**, such as planetary coordinates, ascendant vectors (*Lagna*), and lunar metrics (*Tithi* and *Nakshatram*). The architecture employs **dynamic feature selection**, where specific subsets of these attributes are piped into the modules based on the required **decision logic**.

1. The Preliminary Classification Layer: lagnaStatus

The pipeline initiates with the lagnaStatus module, which functions as a **binary gatekeeper**. It maps planetary coordinates onto a spatial house-based grid (*Rashi* chart). The module applies a **hard-constraint filter**: if the feature set detects malefic variables (*Papa-Grahas*) within the *Lagna* node, the system triggers an immediate **rejection signal** (False) and terminates the execution thread. A rejection is also triggered by "mixed-signal" configurations (simultaneous benefice and malefic presence), ensuring the **model's sensitivity** to conflicting astrological inputs.

2. The Heuristic Optimization Layer: rahitamStatus

The second phase, rahitamStatus, implements a **numerical feature-weighting algorithm**. It computes a composite sum of the *Lagna*, diurnal, and lunar vectors, followed by a **modulo-9 transformation** to derive a core heuristic value.

- **Strong Positives:** Remainders of $\{0, 3, 5, 7\}$ result in immediate progression.
- **Hard Negatives:** Remainders of $\{1, 2\}$ trigger a strong rejection.
- **Conditional Logic:** For values $\{4, 6, 8\}$, the system performs **nested inference**, making the decision contingent upon the weighted strength of the *Lagna* feature.

3. The Deep Inference Engine: basic_computations

The final module, basic_computations, performs a comprehensive **spatial analysis** of all nine planetary vectors relative to the *Lagna* and their corresponding *Adhipathi* (ruling) nodes. The system evaluates the **state-space configuration** against established astrological benchmarks. Specific **adversarial patterns**—such as the Moon or Venus occupying the 6th, 8th, or 12th house nodes—act as **dropout conditions**, leading to model rejection.

Once the **logic-based inference** is complete, the Muhurtam status is predicted and converted into a **numerically encoded format** suitable for supervised learning. To benchmark the system's **generalization capability**, the dataset undergoes a **randomized train-test split**. The resulting **classification model** is evaluated using standard **Machine Learning metrics**, including:

- **Accuracy Metrics:** Quantifying the precision of astrological predictions.
- **Confusion Matrix:** Analyzing Type I and Type II errors to detect bias in the heuristic rules.
- **Data Visualization:** Generating high-resolution plots to identify **latent patterns** and visualize the variance between **predicted vs. ground-truth** Muhurtam strengths.

This computational approach effectively transforms traditional belief-based reasoning into **scalable, interpretable machine-intelligence architecture**.

3.1 Algorithm Pseudo-code:

x: a dataset of Item size 'r' (number of rows) with 25 attributes
y: target variable with Item size 'r'
for h in 0 to r-1 do begin
mStatus: Initialized with status as 'Rejected'
list1: an empty list that is used to capture rashi-wise planets
Identify the lagnaStatus based on the positions of planets.
If lagnaStuas is False do
Muhurtam is rejected and exits from the algorithm
Else

Identify the rahitamStatus based on inputs day, time, Lagna, and nakshatra values.
If rahitamStatus is False do
Muhurtam is rejected and exits from the algorithm
Else
call basic_computations to segregate the planets as either positive or negative
If positive > negative do
Assign mStatus as 'Accepted' and CalculatedStatus =1
Else
Identify the strength of negative planets and still
if positive < negative do
Assign CalculatedStatus = 3
Else
Assign mStatus as 'Accepted, but Weak' and CalculatedStatus =2
End If
End If
End If
End If
End loop
Decompose the dataset as train_data and test_data with split size as 0.25 and randomness is True
Model the algorithm to generate a Classifier model using train_data
Compare the predicted target variable with test_data
Generate Confusion Matrix and find the accuracy of the algorithm
Visualize the algorithm as per the requirement

5. DATA SETS

The data-driven phase of this research utilizes two primary **high-dimensional datasets**. The initial corpus, specifically curates for **Muhurtam optimization**, is structured as a **comma-separated variable (CSV)** file (as visualized in **Figure 1**). This dataset functions as the **input feature matrix**, containing the critical astrological parameters necessary for the **inference engine**. A key attribute within this schema is a labelled column representing the **ground-truth strength** of each Muhurtam.

During the execution of the **predictive pipeline**, our proposed algorithm processes these input vectors to compute a **quantitative strength metric**. These generated outputs are then dynamically integrated as a **new feature column** within the **Python-based data frame**. This synthesized representation facilitates downstream **statistical validation** and **comparative analysis** between predicted values and observed targets.

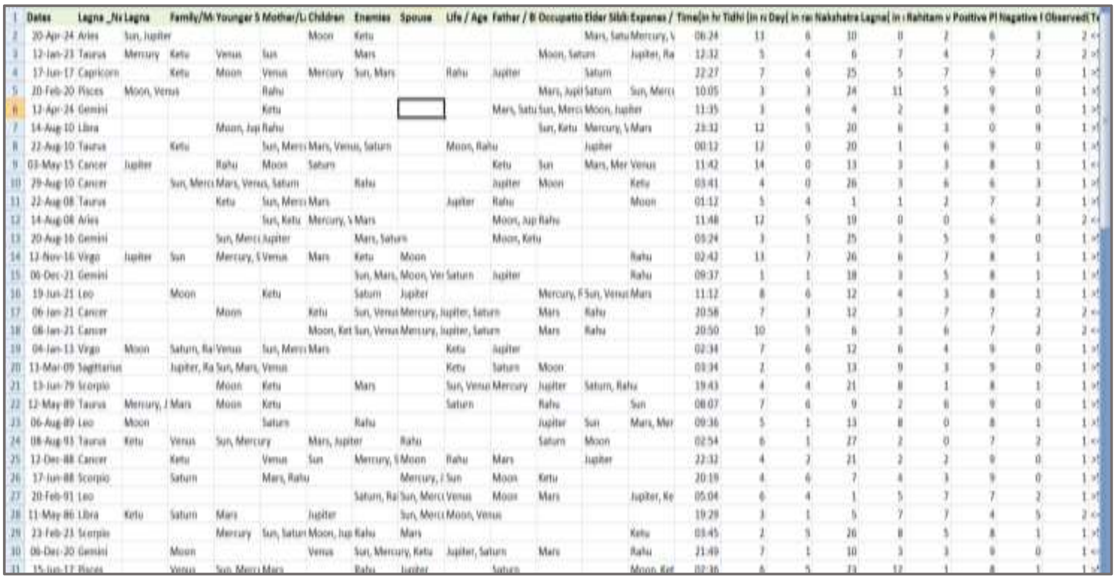

Figure 1. Astrological data collection in CSV format is required to calculate Muhurtam strength. The dataset should include the date, planetary positions according to the horoscope chart, time, and other essential numerical values such as day, tithi, nakshatra, and lagna.

The second dataset functions as a **relational knowledge graph**, encoding the complex inter-planetary dependencies that govern the model's internal logic. This dataset performs **categorical feature mapping** for planetary relationships, classifying each celestial entity's interaction with others into discrete **labels**: *enemy*, *neutral*, or *ally*.

Furthermore, this dataset serves as a **domain-specific reference schema** (as illustrated in **Figure 2**), providing critical **attribute data** for each planet, including:

- **Canonical Sign Mapping:** The planet's primary ownership (*Rashi*).

- **Positional Valence:** Feature vectors representing favourable (**positive**) and unfavourable (**negative**) sign placements.

By integrating these relational and positional variables, the framework can perform higher-order **feature cross-analysis**, allowing the **inference engine** to weigh planetary interactions as weighted inputs within the overall **predictive architecture**.

Planet	Equals	Friends	Enemies	Positive Rashi	Negative Rashi	Own Rashi
Sun	Mercury	Moon, Mars, Jupiter	Venus, Saturn	Aries	Libra	Leo
Moon	Mars, Jupiter, Venus, Saturn	Sun, Mercury	None	Taurus	Scorpio	Cancer
Mars	Venus, Saturn	Sun, Moon, Jupiter	Mercury	Capricorn	Cancer	Aries, Scorpio
Mercury	Mars, Jupiter, Saturn	Sun, Venus	Moon	Virgo	Pisces	Gemini,Virgo
Jupiter	Saturn	Sun, Moon, Mars	Mercury, Venus	Cancer	Capricorn	Sagittarius, Pisces
Venus	Mars, Jupiter	Mercury, Saturn	Sun, Moon	Pisces	Virgo	Taurus, Libra
Saturn	Jupiter	Mercury, Venus	Sun, Moon, Mars	Libra	Aries	Capricorn, Aquarius
Rahu	Jupiter, Mercury	Venus, Saturn	Sun, Moon, Mars	Taurus	Scorpio	None
Ketu	Jupiter, Mercury	Venus, Saturn	Sun, Moon, Mars	Scorpio	Taurus	None

Figure 2. A planetary dataset is required that includes the classification of each of the nine planets along with their corresponding lists of equal, friendly, and enemy planets, as well as the associated Rashis categorized as positive, negative, and own for each planet.

6. RESULTS ANALYSIS

The proposed architecture generates a multi-dimensional output suite, leveraging **tabular data structures** for granular accuracy assessment and **graphical visualizations** for high-level **comparative performance analysis**.

Once the input vectors have been processed through the three-stage **modular pipeline**, the system's primary output is a **binary classification**—represented as a discrete *Acceptance* or *Rejection* state. This decision is derived from a **spatial feature analysis** of planetary coordinates within the horoscope's geometric grid, where the model functions as a **hard-constraint classifier** to determine the final Muhurtam viability.

```
Lagna for Muhurtham is fine, go ahead for next level acceptance
True
Final Rahitam: 4
Muhurtham is strongly rejected as of Rajapanchaka
False
Lagna for Muhurtham is fine, go ahead for next level acceptance
True
Final Rahitam: 7
No issues for Muhurtham w.r.t. Rahitam
True
Capricorn at 9
Capricorn
Aquarius
Pisces
Aries
Taurus
Gemini
Cancer
Leo
```

Figure 3. The initial phase of the algorithm outlines whether a given input is accepted or rejected based on the violation of the Panchaka-Rahitam rule. It also presents the sequence of Rashis beginning with the Lagna.

As illustrated in **Figure 3**, if the candidate Muhurtam successfully clears the **preliminary classification gate**, the system triggers a state transition to the next phase of the **inference pipeline**. In this stage, the algorithm performs a **high-dimensional mapping** of planetary vectors onto their respective **valence-encoded nodes** (*positive* or *negative* Rashis).

The process, detailed in **Figure 4**, functions as a **feature-enrichment layer**, transforming raw spatial coordinates into **interpretive insights**. By aligning celestial positions with established **weighting schemas**, the architecture derives the nuanced **logic-based granularities** required for high-fidelity astrological forecasting.

```
 Sagittarius   Jupiter   1   ['nan']
List of Planets in list 1 [' Capricorn', ' Aquarius', ' Pisces', ' Aries', ' Taurus', ' Gemini', ' Cancer', ' Leo', ' Virgo',
' Libra', ' Scorpio', ' Sagittarius']
No Planet
0
it has planets ['Ketu']
planet Ketu
Ketu
-----------Ketu Mapping-----------
Ketu  is in Negative Rashi
0
it has planets ['Moon']
planet Moon
Moon
-----------Moon Mapping--------
 Aquarius
Moon  is in Positive Rashi place 1
0
it has planets ['Venus']
```

Figure 4. Each house, starting with lagna in the horoscope chart is represented along with the planets it contains, detailing the positive and negative influences of each planet in relation to the respective house.

Upon the deployment of the **AstroClassifier architecture**—a specialized **supervised learning ensemble**—the system generated a comprehensive suite of performance analytics. To rigorously quantify the model's **generalization intelligence**, we derived several critical **evaluation metrics**.

Central to this analysis is the **Confusion Matrix**, which provides a granular breakdown of the model's **classification performance**, identifying the distribution of True Positives and True Negatives against **Type I (False Positive) and Type II (False Negative) errors**. Furthermore, the **global accuracy coefficient** of the algorithm was calculated to assess the overall reliability of the predictive logic. These **validation results** are synthesized and visualized in **Figure 5**, offering a high-fidelity representation of the model's **predictive precision** and **statistical convergence**.

```
print(cm)

[[14  2]
 [ 5 11]]

def compute_accuracy(y_true, y_pred):
    correctly_predicted = 0
    # iterating over every label and checking it with the true sample
    for true_label, predicted in zip(y_true, y_pred):
        if true_label == predicted:
            correctly_predicted += 1
    # computing the accuracy score
    accuracy_score = correctly_predicted / len(y_true)
    return accuracy_score

#y_pred = classifier.predict(x_test)
y_pred = x_test
score = compute_accuracy(y_test, y_pred)
print(score)

0.78125
```

Figure 5. The confusion matrix is generated and subsequently an algorithm is defined to calculate its accuracy using attribute scores. The algorithm determines the correspondence between predicted and computed values to enhance the overall accuracy.

As part of the **post-inference results analysis**, the system generates two distinct **data visualizations** to benchmark the model's performance. The first, illustrated in **Figure 6**, depicts the **cross-entropy** or variance between the **ground-truth labels** (expected status) and the **model-predicted outputs**. This classification is derived from a **spatial feature analysis** of planetary coordinates within the horoscope grid.

The second visualization provides a **geospatial performance comparison**, evaluating the predicted versus observed Muhurtam status relative to the **distribution density** of events within specific geographical coordinates or urban clusters. Furthermore, as shown in **Figure 7**, the **predicted and computed status vectors** are subjected to a **side-by-side evaluation** to detect classification bias.

The **statistical trends** captured in **Figure 8** demonstrate minimal **residual deviation** between the two datasets. This convergence suggests that the proposed architecture has achieved a high level of **predictive accuracy** and **model robustness**, successfully formalizing traditional heuristics into a reliable **computational framework**.

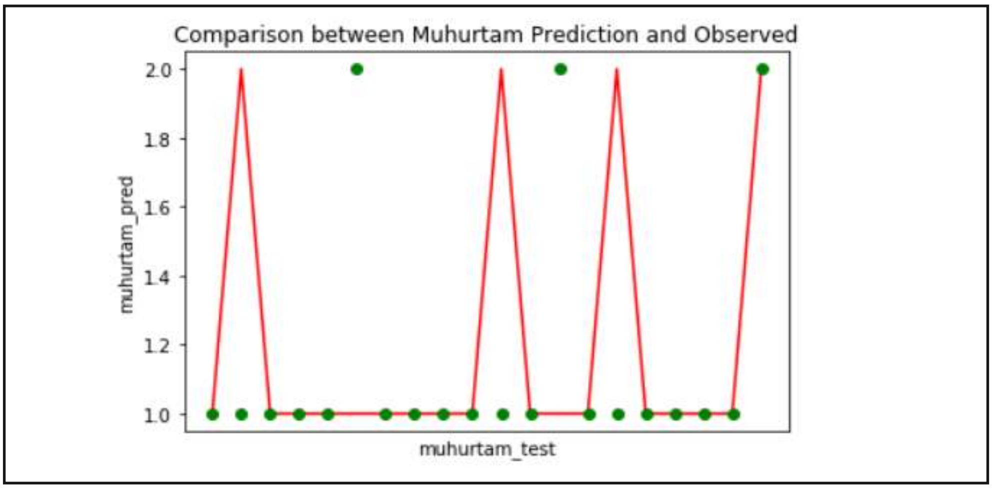

Figure 6. The visualization illustrates the comparison between predicted and observed Muhurtam outcomes, based on both the computational algorithm and the baseline predictions.

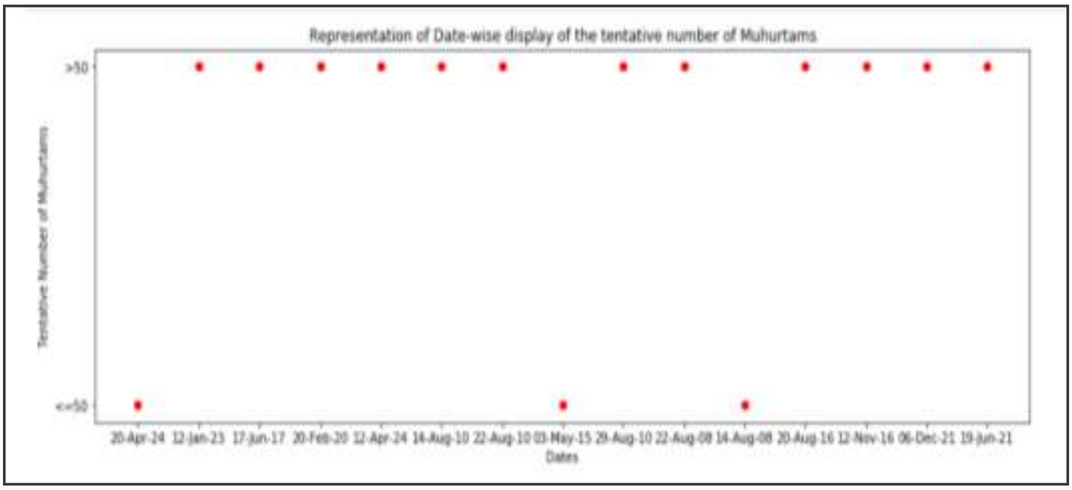

Figure 7. Provides a day wise display of the tentative number of Muhurtams. This breakdown highlights the variation in auspicious timings across different days for easier comparison and selection.

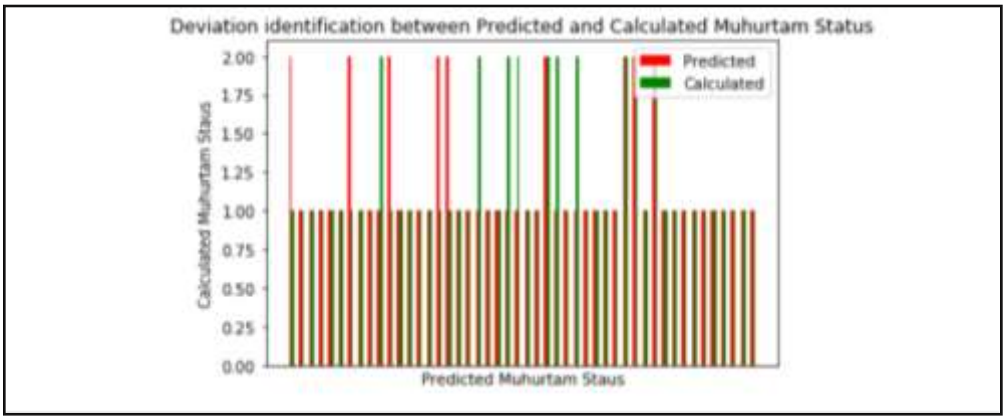

Figure 8. Identification of deviations between predicted and observed Muhurtam status. Visualization highlights the differences to assess accuracy and reliability.

7. CONCLUSION AND FUTURE ENHANCEMENT

Historically, astrology has been categorized as a speculative domain, largely due to a lack of

standardized algorithmic frameworks and **automated logic protocols**. However, the digital media surge has catalyzed a demand for **computational rigor** in this space, driving research to transition from manual heuristics to **automated inference systems**. This study establishes a foundational **rule-based engine** engineered specifically for the **predictive evaluation** of Marriage Muhurtam, utilizing a high-dimensional **input vector** of astrological parameters.

To evolve this **Machine Intelligence** framework, future research will focus on the following strategic vectors:

- **Multi-Agent Parameterization:** Expanding the model to perform independent **feature analysis** for both the bride and bridegroom to calculate a composite compatibility score.
- **Domain Generalization:** Transferring the current **logic-based architecture** to develop specialized modules for diverse events, such as housewarming ceremonies and corporate inaugurations, through **modular rule-set expansion**.
- **Interface Optimization:** Architecting a high-performance **web-based interface** to streamline data ingestion and provide real-time **automated analytical processing**.
- **Explainable AI (XAI) Integration:** Implementing an **interpretive layer** within the UI that provides transparent, logic-based justifications for predicted Muhurtam strength, dynamically mapped to **real-time planetary state-space configurations**.

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