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An Improvised Learning Model with Multi-Layered Cnn for Customized Astrological Prediction System

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Abstract: Numerous applications in the real world require previous prediction and analyses so that crucial decisions can be made to optimise resources, money and time. The ultimate prediction method is astrology, which uses a person's date, time, and place of birth to create a birth chart and reveal the planets' positions. Applications based on astrology serve as a prime illustration of classification strategies. By creating machine learning-based categorization approaches in this work, we solve the issue with traditional astrological tools and forecast the likelihood of occurrence for significant life events like marriage and employment. Then, we put forth an approach that uses a multi-layered convolutional neural network model to recommend events, with an accuracy of greater than 95% and a time required for one epoch of about 1.3 seconds. The suggested approach uses WEKA for processing, which makes the data loaders run considerably more quickly. Consequently, the benchmark dataset used to construct this application was unavailable thus data are collected from diverse people as detailed in the data set generation section and the model was trained accordingly for accurate learning results. Following model training and user interaction validation, the user is prompted for his name, birth date, and sun sign type before receiving an accurate forecast of future occurrences.

Keywords: *Astrology, horoscope, charts, houses, zodiac, classification, multi-layered CNN, philosophies and planets.*

1. Introduction

Planets are in continuous rotation relative to the globe within the sky. There is a significant idea that the locations of the Sun, Moon, & several stars near to planet may reveal people. And it is the fundamental tenet of astrology. The numerous ideologies and philosophies that are now popular vary from one another. There are several names for this astrology method used worldwide. Early advocates of current Indian astrologist, notably Dr. B.V. Raman, called it "Hindu astrologist"

This tests if Astrology is a systematic analysis and use of celestial body language. Larger planet like the Sun, Venus, and other stars are the basis of astrology. It affects human behavior, this is to forecast the changes in our life, as much as the environment, it may affect our sentiments and the moonlight impact the sea, despite the water being far away.

Figure 1: Sample Horoscope chart with house indication

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Table 1: Horoscope's houses and its functionalities

House	Functions
1	Physiological attributes, fundamental drives, well-being, longevity, nature, & the life-affirming vigor that an individual would possess.
2	Pharynx and vision are influenced by the housing. speech is a secondary gift.
3	Boldness, endurance, intelligence, self-esteem, siblings, intellectual ability, jewelry and clothes, and lesser journeys all are governed by this house.
4	Sukhasthan means affluence, a comfortable home, and overall contentment. Old age, private & public issues, and even legacy could be predicted through this house.
5	The fifth sector indicates prospects for children and learning (Vidyasthan). It also controls intelligence and luck.
6	The sixth sector covers enemies, health, & service.
7	The seventh sector has a significant role in determining marital harmony. This bhava encompasses potential commercial alliances as well.
8	This house represents illnesses, death, and difficulties. Additionally, it predicts where illegal income derives from, what they will feel mental, how they will pass away, and their chances of being caught.
9	The benefits of this sector are knowledge, success, renown, and further education.
10	This home represents the father, the career, and the entire prestige a person will acquire over their lives. A person's employment and other extracurricular activities determine their honor, power, and authority.
11	The eleventh sector is concerned with earnings, financial gains, and collected riches. The traits described above also include honor and economic achievement, thus they are also described below.
12	Private adversaries, charity, bed pleasures, grief, spending, losses, and liabilities are ruled by the twelfth sector.

The chart is having the arrangement of the dwellings is in the set. It has four rhomboidal buildings (1, 4, 7, and 10) and eight triangle dwellings. The sign emerging at birth is placed in the first sector, or top center rhomboid, and the other symbols are placed in regular sequence, counterclockwise.

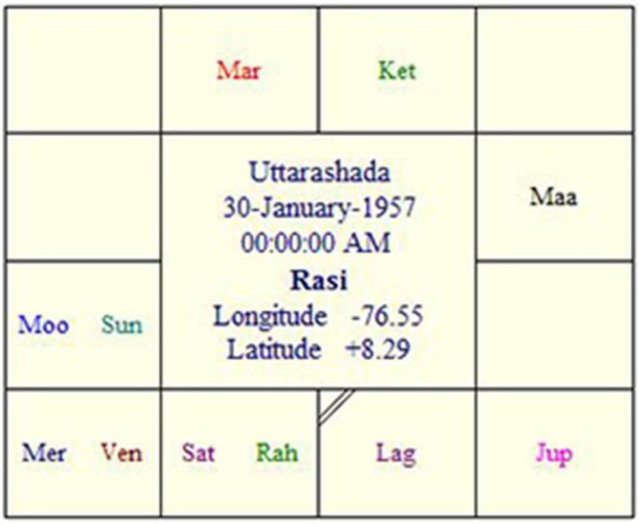

Figure 2: Sample horoscope chart

From figure 2, each horoscope has twelve planets, twelve signs, and twelve houses. All these various angular configurations are produced based on their positioning. A horoscope has 13 attributes: Ascending symbols and planet signs. It is possible to include a 14th characteristic to the list to indicate the horoscope's kind, such as a politician, a doctor, etc.

Table 2: Prediction sample for above sample horoscope chart

Characteristic	Limitation	Types of Data sets in numbers
Ascendant	NOT NULL	2
sunven		0
sunmar		1
sunsat		0
sunmoon		0
sunmerc		0
Sunjup		3
sunura		1
marsat		1
marven		1
mercven		0
vennep		1
sunnep		1
moonven		0
moonmer		0
moonmar		1
moonjup		3
moonsat		0
marura		2
moonura		1
moonnep		1
marmer		1
merjup		3
mersat		0
merura		1
mernep		1
venjup		3
Vensat		0
venura		1
marjup		4
Satnep		3
Uranep		2
Jupura		1
jupsat		2
marnep		2
jupnep		1
satura		0
type		Engineer

2. Review of related works

Day & night, the changing of the seasons, and tidal impacts are all manifestations of planetary influences. There is no doubt that the planets and stars have an impact on our daily lives. Based on the stars' configuration at childbirth, astrologers might identify a person's career trajectory. Astronomy should be true if it's survived for centuries. There is a ton of material on astrological, but its scientific viability has never been shown. After the fifteenth century, a study was done to demonstrate astrology's empirical legitimacy.

Some scholars hold the opinion that astrological is not a science [1] [2], while others feel that further research is necessary to draw that conclusion[3]. Astrology has both predicted & non-predicted aspects, making projected astrology the ideal subject matter for research into the predictive value of numbers [4]. SVM classifier approaches in AI [5] work well for classification & regression problems. It works effectively even with very hazy and ambiguous data. Climate forecasting [6], disease diagnosis and diagnostics [7], machine translation [8], and other industries have all made use of these approaches. A brief survey of techniques for ML and implementations is provided in [9]. By utilizing multiple learning algorithms to enormous amounts of data on people's planetary positions and autobiographies, a system may predict numerous elements of human existence.

No research has been conducted to forecast human existence dependent on planet placements using AI. Then developed an approach for music recommendation utilising the BiLSTM model, achieving an accuracy of 83% and a time to first epoch of roughly 1.4 seconds, while also suggesting the usage of CUDA for the model's processing, which speeds up the data loads [10]. Some basic work utilizes Case-Based Reasoning & closest neighbor technique. This paper used a person's date of birth, time of birth, and place of birth to project whether or not they would be hired by the government. They gathered data from 100 persons, 50 of whom are government officials and the rest of whom are private sector workers. They used a machine learning tool to compute and compare the accuracy of various classification strategies [11].

2.1 Problem Formulation

On the data used to forecast a person's profession astrologically, learning algorithms may be employed. Acquiring the information and extracting the elements that will be instructive and beneficial are the fundamental procedures utilized for tissue development. Once the database is prepared, several unsupervised learning techniques will also be used to make predictions.

2.1.1 Data sets gathering and extraction

The writers obtained the information from 24 players, 24 singers, and 10 scientists by consulting credible sources. Date, time, location, occupation, learning, and a short life history of the subject were all obtained. Based on Indian astronomy, astronomical calendars then were created. These planet diagrams were made using time, date, and location of origin. Then, for later use, these records were archived in table format. Relevant analytical attributes were extracted and preserved in the test suite. 23 characteristics in all were taken into account and utilized for categorization. Table 3 describes the characteristics used to forecast a person's career using classification models. Most characteristics are of the conceptual kind, based on the planets' and zodiacs' placements in astrology at the moment of the person's birth.

Table 3: Attributes used for classification tasks

Characteristics	Model	Explanation
Aries	Nominal	Aries's astrological house number. Values in between 1 and 12.
Taurus		Taurus astrological house number. Values in between 1 and 12.
Gemini		Gemini astrological house number. Values in between 1 and 12.
Cancer		Cancer astrological house number. Values in between 1 and 12.
Leo		Leo astrological house number. Values in between 1 and 12.
Virgo		Virgo astrological house number. Values in between 1 and 12.
Libra		Libra astrological house number. Values in between 1 and 12.
Scorpio		Scorpio astrological house number. Values in between 1 and 12.
Sagitarius		Sagitarius astrological house number. Values in between 1 and 12.
Capricorn		Capricorn astrological house number. Values in between 1 and 12.
Aquarius		Aquarius astrological house number. Values in between 1 and 12.
Pisces		Pisces astrological house number. Values in between 1 and 12.
Sun		Sun astrological house number. Values in between 1 and 12.
Moon		Moon astrological house number. Values in between 1 and 12.
Mars		Mars astrological house number. Values in between 1 and 12.
Mercury		Mercury astrological house number. Values in between 1 and 12.

Venus		Venus astrological house number. Values in between 1 and 12.
Jupiter		Jupiter astrological house number. Values in between 1 and 12.
Saturn		Saturn astrological house number. Values in between 1 and 12.
Rahu		Rahu astrological house number. Values in between 1 and 12.
Ketu		Ketu astrological house number. Values in between 1 and 12.
Gender		M : Male or F: Female.
Class		It holds one of the three different values, Player, Musician, or Researcher.

2.1.2 Data Processing and transformation

It is an ML program designed in Java by Waikato University. WEKA is a software program that is made available underneath the GNUs License. It includes visualizations, techniques for information processing, and GUI.

The document in the ARRF structure utilized by Weka was constructed from extracted data in step 1. The characteristics and various values were described to generate the files. Then, data points were put from every line utilizing comma-separated formatting.

3. Proposed Methodology: Construction of MCNN

In this part, we explicitly go over the RHRM structure shown in Fig 2. A review semantically extracts, a user profile creator, and a user/item recommendations creator make up our application's 3 phases. The review's usefulness is categorized during the initial stage. CNN-BiLSTM combination model generates review semantic information and classifies review helpfulness [12,13]. The second step results in a profile of the user comprising of nothing but events between users and the item that matches to positive ratings given by the user. The most well-liked CF approaches were used in the last stage to predict users' type depending on their connections history. We begin by outlining every phase's specifics.

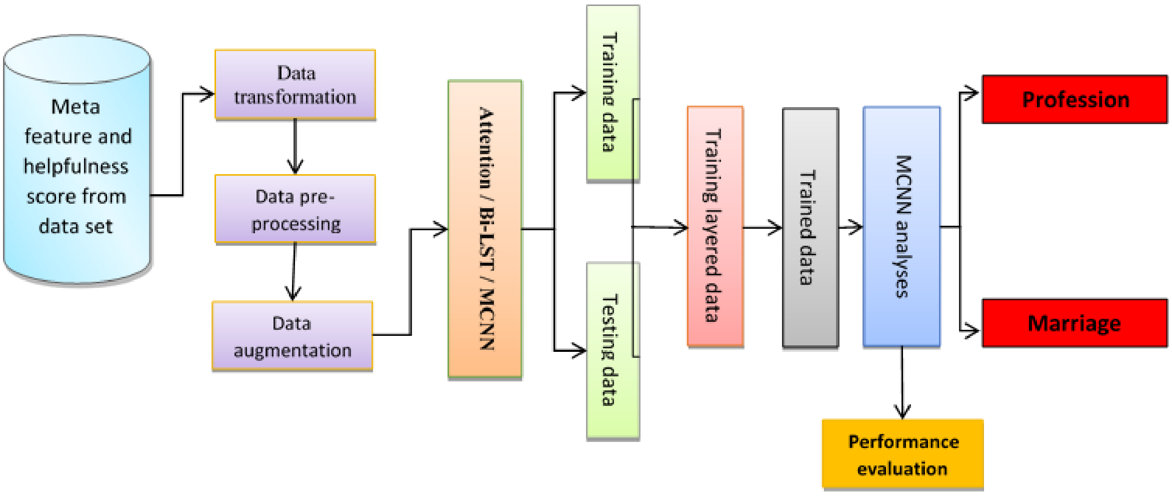

Figure 2: Pipeline flow of proposed MCNN

Stage 1: Attribute extraction principle

The first phase develops a CNN-BiLSTMs hybrid approach for review utility. The CNN-BiLSTMs model layout viewpoint is shown in Fig. 3. This study creates a CNN-BiLSTMs hybrid approaches information in quality [14,15]. CNN reduces input characteristics for forecasting, and the connection across each phrase and a final category varies [16,17]. The BiLSTM encodes long-distance word relationships. Due to each of these benefits, several hybrid CNN-BiLSTM approaches have been put out [18,19]. This research employed CNN-BiLSTMs. Current models used the CNN and the BiLSTMs networks. The approach has been used for regression model on integer information and classification challenges. We employed filtering kernel and innovative focus technique levels to retrieve the text [20,21]. After creating review-level semantics, the study classified constructiveness.

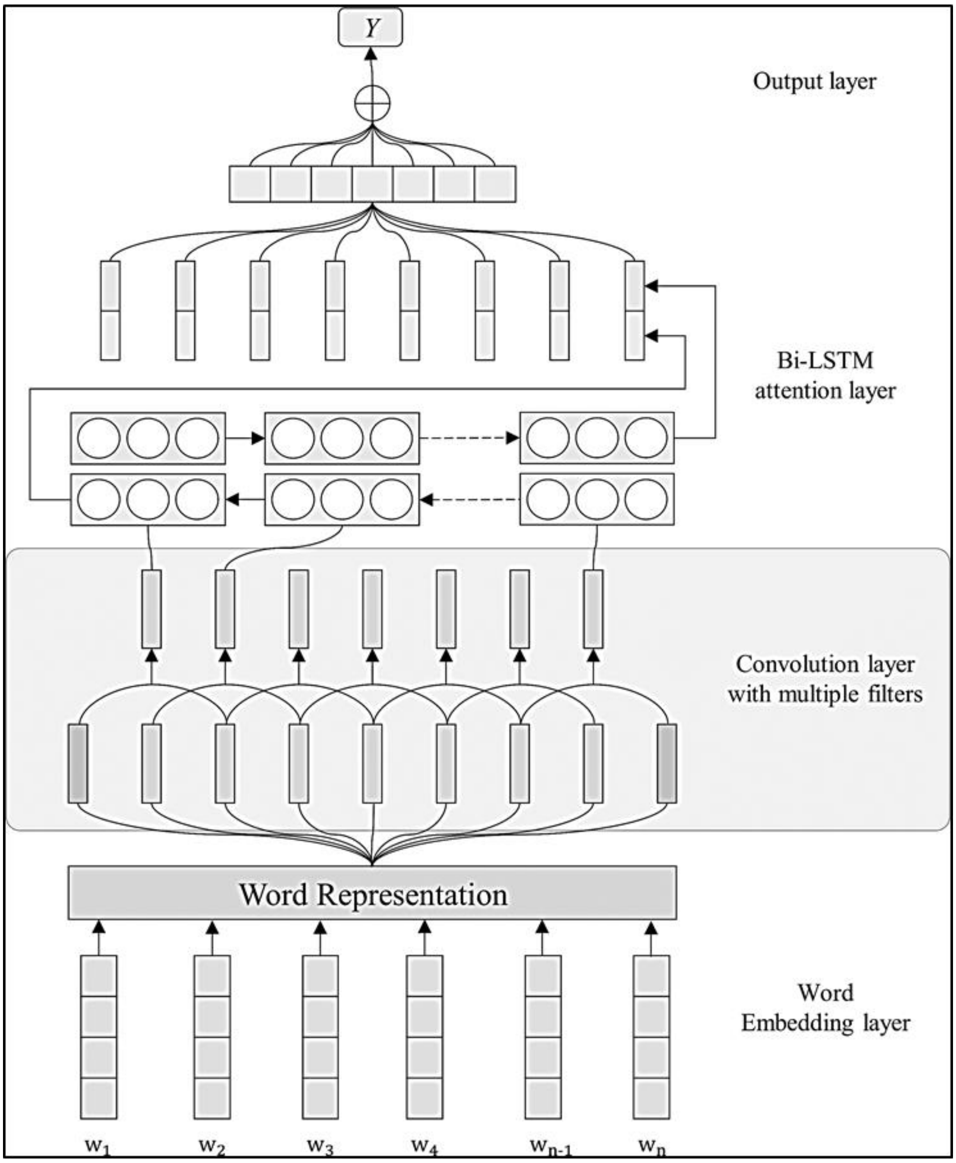

Figure 4: CNN–attention to BiLSTM's mechanism design.

In this work, we used $\mathcal{R} = \{r_1, r_2, \cdots, r_n\}$ to build a CNN-BiLSTM hybrid approach with attention. Each review has five characterizations: P for the controller is designed, U for reviewer functionalities, C for feature sets, and M for metadata functionalities. H: total vote vs helpful vote, where H[0,1]. Let F be an nm information matrix, n be the no of reviews & m be the total no. of characteristics. Z be embedded matrix contains expected values of an review, where Z_i denotes how useful a review is. Last but not least, we establish helpfulness control limits of Θ_1 and Θ_2. As a result, Z i is derived as follows:

$$Z_i = \begin{cases} 1, & \text{if } H_i > \Theta_1 \\ 0, & \text{if } H_i < \Theta_2 \end{cases} \quad (1)$$

This study creates a hybrid CNN-BiLSTMs model to predict Z given F. The developed algorithm forecasts the relevance rating of reviews posted with unreported values. .

Three layers make up CNN-BiLSTM. Word embedding is the initial layer. Let$R_{u,i} = \{w_1, w_2, \cdots, w_n\}$ indicating that user u has published the comment for the item i in which n is the duration of the review. The one-hot encoding technique was primarily used by several of the current text-mining methods to turn every phrase into a matrix. In this procedure, the matrix lengths are excessively big and most vector values are zero. Every phrase used in the investigation was transformed into a vectors type using the word encoding layers. To represent every phrase in the article as a heavier load, word-based $f: w_n \to R^D$ has been employed in this work. A matrices $E \in R^{n \times d}$, where d is the size of the phrase embedded vectors, is then used to describe the proving.

The second layer is convolution. It filter$K_j$with a moving window to computation. It is possible to describe the convolutional activation method using here.

$$c_j = \phi\left(E * K_j + b_j\right), \tag{2}$$

where * indicates convolutions, $K_j \in R^{k \times m}$ represents kernel parameters, and k*m specifies kernel size. $b_j$represents bias, and ReLU be the activation function, which would be specified as here.

$$\text{all}(x) = \text{m}\ \ (0, x) \tag{3}$$

Where adding max-pooling to convolution's result preserves interpretation and reduces noise. The calculation is used to define the max-pooling procedure.

$$O_j = \text{m}\ \ \left(\left[c_1, c_2, \cdots, c_{(l-t+1)}\right]\right) \tag{4}$$

The numerous lexical features found in the analysis were extracted using some filters, each of varying sizes. The convolutional layer's outcome is expressed as.

$$O = [o_1, o_2, \cdots, o_n] \tag{5}$$

Every variable in the convolved result represents a BiLSTM simulation time. BiLSTM has forward and reverses LSTM. The forward LSTM catches left-to-right review semantics while the reverse LSTM collects the right-to-left sequence. The outputs generated by the forward and backward LSTMs are referred to as $\vec{S}_t$ and $\overleftarrow{S}_t$, etc, in this work. To produce two distinct hidden layer patterns, we used Bi-LSTM for the evaluation of each term included in the route sequence. Let's assume that the specified incoming signal is $\{o_1, o_2, \cdots, o_n\}$ and that "$\{\vec{S}_1, \vec{S}_2, \cdots, \vec{S}_t\}$and $\{\overleftarrow{S}_1, \overleftarrow{S}_2, \dots, \overleftarrow{S}_t\}$ are generated by the reverse and forward LSTMs, respectively.

$$\vec{S}_t = \text{LSTM}\left(\vec{S}_{t-1}, O_t\right) \tag{6}$$

$$\vec{S}_t = \text{LSTM}\left(\vec{S}_{t-1}, O_t\right) \tag{7}$$

$$m = \left[\vec{S}_l; \vec{S}_{t-1}\right] \tag{8}$$

The BiLSTM joins the last forward and first backward hidden states to form the final approximation. For effective ordering capture, the embedded vector m contains both forward and backward route information. We added an attentive method layer to CNN-BiLSTMs to collect review features and highlight relevance factors. The research is a part of the Equation-defined feed-forward long short - term memory (9)

$$h_t = \sigma(m_i) \tag{9}$$

$$a_t = \frac{\exp(h_t)}{\sum_{i=1}^{n} \exp(h_t)} \tag{10}$$

$$Q = \sum_{i=1}^{m} a_t \cdot m_i \tag{11}$$

where m_t is the BiLSTM structure's eigenvalue outputs and is the attentive training nonlinear activation tanh. The weight of the measured created attentiveness is denoted by h_t. The model's participation in the path while responding to a query relationship is shown by the matching score, a_t. The weighted sum procedure employs SoftMax to produce attention probability. Q denotes a merger of the description, attentiveness probabilities, and m_t previously hidden interpretation.

This model's goal is to identify the outcomes by computing the relevance score's probabilities dependent on the semantics attribute retrieved from the evaluation, which may be specified as Eqn (8).

$$Y = \theta(W_s \cdot Q + b_s) \tag{12}$$

W_s : weight matrices, b_s : bias. The input feature was given a value of 0 or 1 and transmitted as an outcome. If the result has a value of 0, the evaluation was useless, and if it has a value of 1, it was beneficial.

Stage 2: Profile generation with matching of horoscope houses for user

Updates to user profiles are made based on the user's beneficial evaluations of the object in the second stage, which also makes use of the findings of the categorization of user data. We used the hybrid CNN-BiLSTM model we created in the first step to categorize review relevance data. The revised user profile only includes user/item transactions corresponding to good reviews. Given $\Re = \{r_1, r_2, \cdots, r_m\}$ each review may have five identifications [P, U, C, M], where P and U denote item and reviewer characteristics. Additionally, C is a textual attribute of the new reviews, while M stands for metadata attributes Let $\mathbb{R}_{ui}$ be an N*M information matrix, where N indicates the number of reviews and M is the total features. Y is the embedded vector value in which CNN-BiLSTM forecasts all recent reviews, where Y_{ui} reflects review r_{ui}

$$\mathbb{R}_{ui} = \begin{cases} 1, & \text{if } r_{ui} \text{ (user } u\text{, item } i \text{) ;} \\ 0, & \text{otherwise.} \end{cases} \tag{13}$$

where 1 for $\mathbb{R}_{ui}$denotes a positive evaluation of product i by customer u. Similarly, a value of 0 indicates that the assessment was unsuccessful. We then create a brand-new user account with such a score of 1.

Stage 3: Classification of profession and marriage

Predicting preference ratings using the UBCFs, SVDs, and NCFs approach which are often use in research about customized proposal management—allows us to assess the effectiveness of the suggested recommendation framework.

The UBCF design is the very first. UBCF is the typical neighborhood-based method in the recommendation system. The most popular UBCF, sim(u,v), and gauges likely have a good [22,23]. This method aims to estimate the user's preference rating for the item I, or p_{ui}. We determine the products that user u regarded as being most similar to the user I using the similarity metric. The anticipated rating is calculated as the weighting factor of the neighboring users' evaluations, as follows:

$$\hat{r}_{ui} = \bar{r}_u + \frac{\sum_{v \in N_i^k(u)} \operatorname{sim}(u,v) \cdot (r_{vi} - \bar{r}_v)}{\sum_{v \in N_i^k(u)} \operatorname{sim}(u,v)} \tag{14}$$

The SVD model comes in second. The great reliability and adaptability of the latent semantic method have helped it become more popular. This research examines the SVD of the interaction matrices. The most frequent method for calculating interaction variables is matrix rearrangement [24,25]. Each user's latent variable vector is connected to an item's latent factor vector using a standard method that is often utilized in research. This method often uses explicit feedback information to solve overfitting problems with formalized models. The following defines the SVD model:

$$\min_{U.V} \parallel Y - M \odot (UV) \parallel_F^2 + \lambda(\parallel U \parallel_F^2 + \parallel V \parallel_F^2), \tag{15}$$

wherein U & V are the numbers of latent variable consumer & objects, λ regularizes the framework. Y : values set, M : binary mask.

The NCF design is third. In traditional latent variable methods, vector dot items estimated hidden scalar associations. Therefore, such a plan cannot provide exceptional results. NCF model combines user item hidden variables utilizing multi-layer synapses. Multi-layer perceptrons may predict customer preferences by using the latent vectors of the person and the item as inputs. The model learns by decreasing the difference between predicted and actual scores. The NCF prediction model is described as follows:

$$\hat{r}_{ui} = f\left(U^T \cdot s_u^{user}, V^T \cdot s_i^{item} \mid U, V, \theta\right), \tag{16}$$

wheres_u^{user} and s_i^{item} signify that the input image has two feature vectors. The latent components for the user and the product are denoted by U and V, correspondingly, while the suited for a particular is denoted by θ.

4. Experimental results and discussion

The above approach produced data that was imported into the Weka tool. Then, using a ten and twelve fold cross validation, several classification techniques, including Hybrid CNN and NADE

CNN, CNN and KELM, Deep CNN with data augmentation, CNN and Genetic Algorithm, ZeroR, Decision Table and MCNN Network model (proposed), were applied to the data. Table 4 lists the precision, accuracy, f-measure, ROC, error rate, MCC and recall values that each approach obtained. The comparison of mistakes produced by approaches is shown in Figure 1. Figure 2 displays a graph of correctly and incorrectly classified items using different categorization methods. For these circumstances, proposed model with 12-fold validation yielded the best results. Figure 5's graph provides insight into the accuracy by describing the errors produced by different astrological prediction systems. The right and incorrect results produced by various categorization approaches on the data is also depicted in figure 5's graph.

Table 4: Analysis of various performance measures

Methods	Accuracy	Precision	Recall	F-measure	ROC	Error rate	MCC
	Percentages						
Hybrid CNN	96%	94.5	94.7	94.6	0.9	0.089	0.4656
CNN	96.2%	95.7	95.7	95.5	0.9	1.02	0.4534
KELM	93.7%	83.5	76.6	73	0.9	1.56	0.4317
Deep CNN	94.6%	81.3	76	78	0.9	1.63	0.4658

CNN with Genetic Algorithm	94.3%	92	96.7	94.3	0.8	0.077	0.4205
ZeroR	96.1%	95.8	95.7	95.7	0.9	0.075	0.3564
Decision Table	98.9%	99.6	99.2	99.2	0.9	0.065	0.2645
MCNN Network model (proposed)	99%	100%	100%	99.6%	0.9	0.055	0.1253

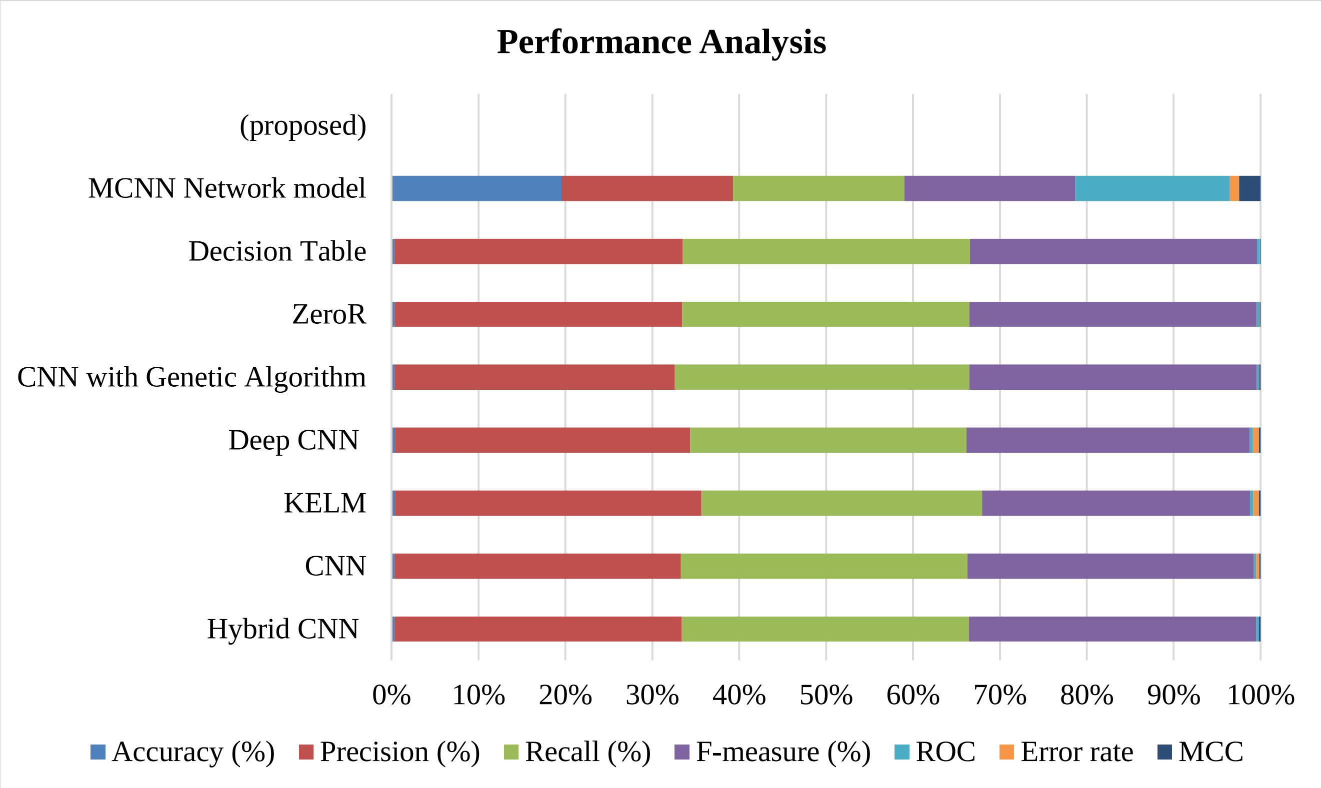

Figure 5: Performance analysis of proposed work

In Table 4, a variety of metrics, including prediction accuracy, recall, precision, F-measure, ROC, error rate, and MCC, are compared to one another. The prediction accuracy of the layered network model is 99%, which is greater than hybrid CNN, CNN and KELM, deep CNN, CNN-GA, ZeroR, and Decision Table by 4%, 2.7%,5.5%,4.2%, 4.4%, 4.3%,2.9%, and 0.21% respectively. The precision of the multilayer network is 100 percent, which is higher than that of hybrid CNN, CNN, KELM, deep CNN, CNN-GA, ZeroR, and Decision Table by 5.1%, 4.9%, 16.5%, 18.5%, 7.8%, 4.8%, and 0.51% respectively. The layered network model has a recall of 100%, which is greater than hybrid CNN, CNN, KELM, deep CNN, CNN-GA, and ZeroR by 5.6%, 5.8%, 23.05%, 25.2%, 3.8%, 4.6%, and 0.845% respectively. The F-measure for the layered network model is 99.45%, which is greater than hybrid CNN, CNN, KELM, deep CNN, CNN-GA, ZeroR, and the Decision Table model by 4.4%, 4.4%, 27.05%, 21.06%, 5.5%,3.5%, and 0.42% respectively. The relative accuracy coefficient (ROC) of the suggested layered network mode is significantly greater than that of other ways; specifically, it is 0.13, 0.15, 0.140, 0.180, 0.20, and 0.17, which is significantly higher than other approaches. The proposed model has an error rate that is 0.05, which is lower than the error rates of existing techniques. However, the proposed model yields a better MCC value of 0.1253, while the others are 0.466, 0.454, 0.417, 0.458, 0.425, 0.354, and 0.265 accordingly. In general, the MCC value should range from -1 to 1. (See Fig 5).

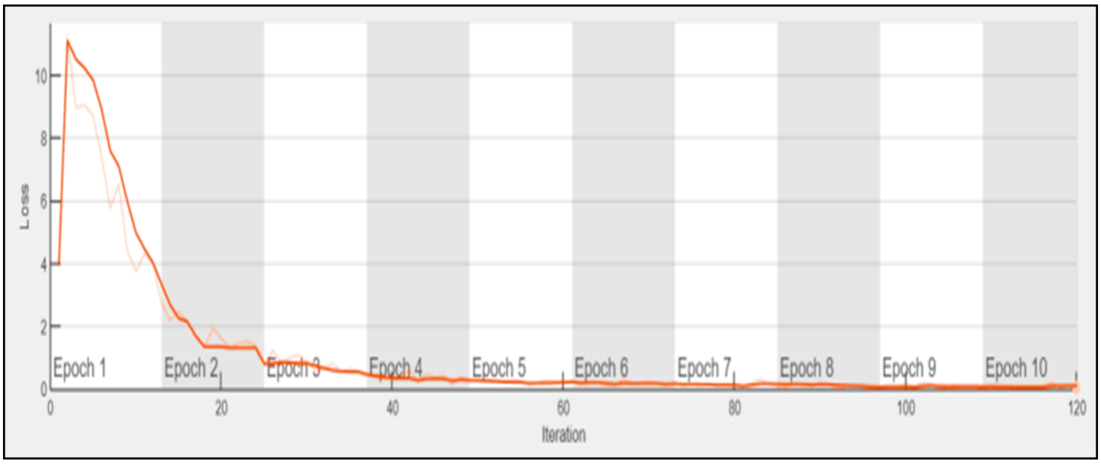

Figure 6: Loss curve for 10 epochs

Figure 6 shows better loss curve as because of the usage of 'learn_curve' opration to get a best fit archetypal setting with the help of converse regularization parameter and so hyper parameter tuning time can be reduced while getting the classification result.

5. Conclusion

From the outcomes section, it is clear that the proposed MCNN model with 12 folds cross validation generated the greatest results with 98.6% accuracy, it can be argued that it is superior to other algorithms presented for predicting a person's profession. A database established before may be used as input by the WEKA method, from which a neural network model may be constructed. The nature of the new horoscope is then predicted using this model. When a fresh horoscope is tested (considered as a Test set), WEKA builds a strategy from the Training phase and uses that model to make predictions. Because the proposed achieved better results, real-time application of the technique is very likely. Additionally, various pairs of qualities can be found and chosen, which might result in more relevant results. Using the suggested classification algorithms, we have conducted predictions for the person's job and marriage. The fundamental character of a person, their attitude, their financial situation, their family, and other aspects of their life can also be predicted.

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