Predictive Modeling for Spacecraft Collision Avoidance Using CNN and RNN Architectures

1. Introduction

1.1 Overview of Spacecraft Collision Prediction

Predicting spacecraft collisions is an essential aspect of space operations, aimed at forecasting the potential risk of collisions between active satellites and other space objects, such as inactive satellites and space debris. Accurate predictions are crucial for collision avoidance maneuvers, preventing costly damages and ensuring the longevity of space missions. This process involves leveraging validated space surveillance data to analyze historical conjunction data messages (CDMs) and identify potential collision threats.

1.2 Importance of Predictive Modeling in Space Operations

Predictive modeling plays a critical role in space operations by providing tools to anticipate potential collisions and manage risks effectively. The space environment is highly dynamic, with a significant number of objects orbiting Earth, including more than 34,000 objects larger than 10cm. Advanced predictive models, especially those utilizing machine learning, can capture the complex relationships within this data, providing more reliable forecasts and enhancing collision avoidance strategies.

1.3 Objectives of the Report

The objectives of this report are to:

1. Provide a comprehensive overview of spacecraft collision prediction methods.
2. Examine the roles of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) in improving prediction accuracy.
3. Detail the process of data collection, preprocessing, and model training.
4. Evaluate the models' performance and compare them with traditional methods.
5. Offer insights and recommendations for future research and practical applications.

2. Literature Review

2.1 Historical Background of Spacecraft Collision Prediction

Historically, spacecraft collision prediction has relied on manual tracking and basic statistical methods to identify potential collision risks. The advent of more sophisticated space surveillance networks and the proliferation of space objects necessitated more advanced techniques. Traditional methods involved simple probability calculations based on object trajectories, but as the number of orbiting objects increased, the need for more accurate and automated prediction methods became evident.

2.2 Overview of Machine Learning in Space Operations

Machine learning has transformed the analysis of space operations data. Algorithms such as support vector machines (SVM), decision trees, and neural networks have been applied to predict collision risks. These models can learn from vast amounts of historical CDMs, identifying patterns that traditional methods might miss. The integration of machine learning into space operations has led to significant improvements in prediction accuracy, thereby enhancing collision avoidance measures.

2.3 Introduction to CNN and RNN Models

Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are two types of neural networks that have shown promise in time-series forecasting tasks. CNNs are well-suited for spatial data and can capture local patterns effectively, while RNNs, particularly Long Short-Term Memory (LSTM) networks, are designed to handle sequences and retain information over long periods. These characteristics make CNNs and RNNs suitable for analyzing the temporal dynamics and sequential nature of CDMs in spacecraft collision prediction.

2.4 Comparative Analysis of Different Predictive Models

Various models have been employed for spacecraft collision prediction, each with its strengths and limitations. Traditional models like the Probability of Collision (Pc) are effective for straightforward scenarios but struggle with complex, non-linear patterns. Machine learning models such as decision trees and SVM offer better performance on non-linear data but may require extensive feature engineering. CNNs excel in capturing spatial patterns within the CDM data, while RNNs, especially LSTM networks, are adept at handling the temporal dependencies inherent in the CDM sequences.

Several predictive models have been employed for spacecraft collision prediction, including:

- **Probability of Collision (Pc)**: A traditional method based on object trajectories and covariances.

- **Support Vector Machines (SVM)**: Used for classification and regression tasks, capable of handling non-linear data.

- **Convolutional Neural Networks (CNN)**: Effective for spatial data analysis, capturing local patterns in CDMs.

Comparative studies have shown that while traditional methods like Pc and SVM have their merits, CNNs and RNNs often outperform them in terms of accuracy and the ability to handle complex, long-term dependencies in the CDM data.

3. Project Details

3.1 Abstract

Today, a typical satellite in Low Earth Orbit (LEO) reports hundreds of danger alerts every week for close encounters with other space objects (such as satellites, space debris, etc.). According to estimations done by the European Space Agency (ESA) in January 2019, more than 34,000 objects larger than 10 cm are orbiting our planet. Of these, 22,300 are tracked and their position released in a globally shared catalog. After processing and filtering the collected data, the most potentially dangerous encounters must be followed up in detail by an analyst with expert knowledge in the field. On average, more than one collision avoidance maneuver is performed on each satellite every year. This report focuses on leveraging machine learning models, specifically Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN), to improve the prediction accuracy of potential spacecraft collisions. By analyzing historical conjunction data messages (CDMs), these models can capture complex patterns and temporal dependencies that traditional methods may miss. The study outlines the process of data collection, preprocessing, feature selection, and the implementation of RNN and CNN models.

3.2 Technologies Used

Python: Programming language used for implementation.Libraries:

NumPy: For numerical operations and array manipulations. Pandas: Data manipulation and analysis library.

Matplotlib: Plotting library for visualizing data.

TensorFlow: Deep learning framework for building and training models.

Keras: High-level API that works on top of TensorFlow for building neural networks.

scikit-learn: Machine learning library for data preprocessing and evaluation.

3.1 Methodology

To accomplish this project we have synthesized the work process in 6 steps. These steps are not only sequential, since, as we will see later, we have

approached the problem from several different perspectives that had their specific necessities. Hence the steps described below are more similar to an iterative process.

1. Data Description: This is the first common step for all the proposed perspectives. In it, an attempt has been made to understand the nature of the data, the possible problems or difficulties involved in it, check the type of features available, etc. In short, to understand the data we have.

2. Data Wrangling: Before training the Deep Learning algorithms we have to make sure that the data is correctly transformed and cleaned so that it can be interpreted by the models. Besides, for both of the proposed approaches, it has been necessary to transform the data in a specific way.

3. Feature Selection: Due to the large number of features provided in the dataset, it will be important to check which of them provides more information to the model. In this step, we select these important features according to different criteria. By doing this we also avoid introducing noise into the DL models thus helping their stability and reliability.

4. Feature Engineering: In this step, new features are created to be introduced into the model to help you better solve the problem. The new features can be obtained by brute force (by making mathematical transformations) or from the knowledge that developers have about the data.

5. Deep Learning Modeling: In this last step we create the Deep Learning models, train them, test them and tune their hyperparameters to achieve better results.

4. Data Manipulation

In this section, we will describe the data itself and its main characteristics, as well as the transformations and techniques used to solve the problems encountered and to feed the DL models.

4.1 Data Description

The training dataset contains 162,634 rows belonging to 13,154 unique events. Giving on average about 12 rows per potential collision. Each row corresponds to a single CDM, and each CDM contains 103 features related to the objects' spatial positions and velocities, that will be described below.

The dataset is made of several unique potential collision events identified by the event_id column, and each event is made of several CDMs recorded over time. Therefore, each potential collision event can be thought of as a time series of CDMs. For the column description, we will first explain those with a unique name and then those whose name difference depends on whether they are referring to a characteristic of the satellite (columns that start with a t) or the chaser object (columns that start with a c).

4.1.1 **Uniquely Named Columns**

- **risk:** Self-computed value at each CDM on base 10 log. The last value at each unique event, i.e. time-of-closest approach (tca) is the target to be predicted by the models. For the evaluation metric used, an event is considered of **high risk** when its last recorded risk is greater than -6, and of **low risk** when it is less than or equal to -6. Its possible values range from -30 (minimum risk) to 0 (maximum risk).
- **event_id**: Unique id per potential collision event.
- **time_to_tca**: Time interval between CDM creation and time-of-closest approach [days]. Its possible values range from 7 days (maximum time to collision) to 0 days (minimum time to collision).
- **mission_id**: Identifier of mission that will be affected.
- **max_risk_estimate**: Maximum collision probability obtained by scaling combined covariance.
- **max_risk_scaling**: Scaling factor used to compute maximum collision probability.
- **miss_distance**: Relative position between chaser & target at tca [m].
- **relative_speed**: Relative speed between chaser & target at tca [m/s].
- **relative_position_n**: Relative position between chaser & target: normal (cross-track) [m].
- **relative_position_r**: Relative position between chaser & target: radial [m].

- **relative_position_t**: Relative position between chaser & target: transverse (along-track) [m].
- **relative_velocity_n**: Relative velocity between chaser & target: normal (cross-track) [m/s].
- **relative_velocity_r**: Relative velocity between chaser & target: radial [m/s].
- **relative_velocity_t**: Relative velocity between chaser & target: transverse (along-track) [m/s].
- **c_object_type**: Object type which is at collision risk with satellite.
- **geocentric_latitude**: Latitude of conjunction point [deg].
- **azimuth**: Relative velocity vector: azimuth angle [deg].
- **elevation**: Relative velocity vector: elevation angle [deg].
- **F10**: 10.7 cm radio flux index [10^{-22} W/(m^2 Hz)].
- **AP**: Daily planetary geomagnetic amplitude index.
- **F3M**: 81-day running mean of F10.7 (over 3 solar rotations) [10^{-22} W/(m^2 Hz)].
- **SSN**: Wolf sunspot number

4.1.2 **Shared Column Names Between the Chaser and the Satellite**

- **x_sigma_rdot**: Covariance; radial velocity standard deviation (sigma) [m/s].
- **x_sigma_n**: Covariance; (cross-track) position standard deviation (sigma) [m].
- **x_cn_r**: Covariance; correlation of normal (cross-track) position vs radial position.
- **x_cn_t**: Covariance; correlation of normal (cross-track) position vs transverse (along-track) position.
- **x_cndot_n**: Covariance; correlation of normal (cross-track) velocity vs normal (cross-track) position.
- **x_sigma_ndot**: Covariance; normal (cross-track) velocity standard deviation (sigma) [m/s].
- **x_cndot_r**: Covariance; correlation of normal (cross-track) velocity vs radial position.
- **x_cndot_rdot**: Covariance; correlation of normal (cross-track) velocity vs radial velocity.
- **x_cndot_t**: Covariance; correlation of normal (cross-track) velocity vs transverse (along-track) position.
- **x_cndot_tdot**: Covariance; correlation of normal (cross-track) velocity vs transverse (along-track) velocity.
- **x_sigma_r**: Covariance; radial position standard deviation (sigma) [m].
- **x_ct_r**: Covariance; correlation of transverse (along-track) position vs radial position.
- **x_sigma_t**: Covariance; transverse (along-track) position standard deviation (sigma) [m].
- **x_ctdot_n**: Covariance; correlation of transverse (along-track) velocity vs normal (cross-track) position.
- **x_crdot_n**: Covariance; correlation of radial velocity vs normal (cross-track) position.
- **x_crdot_t**: Covariance; correlation of radial velocity vs transverse (along-track) position.

- **x_crdot_r**: Covariance; correlation of radial velocity vs radial position.
- **x_ctdot_r**: Covariance; correlation of transverse (along-track) velocity vs radial position.
- **x_ctdot_rdot**: Covariance; correlation of transverse (along-track) velocity vs radial velocity.
- **x_ctdot_t**: Covariance; correlation of transverse (along-track) velocity vs transverse. (along-track) position.
- **x_sigma_tdot**: Covariance; transverse (along-track) velocity standard deviation (sigma) [m/s].
- **x_position_covariance_det**: Determinant of covariance (~volume).
- **x_cd_area_over_mass**: Ballistic coefficient [m^2/kg].
- **x_cr_area_over_mass**: Solar radiation coefficient . A/m (ballistic coefficient equivalent).
- **x_h_apo**: Apogee (-R_{earth}) [km].
- **x_h_per**: Perigee (-R_{earth})[km].
- **x_ecc**: Eccentricity.
- **x_j2k_inc**: Inclination [deg].
- **x_j2k_sma**: Semi-major axis [km].
- **x_sedr**: Energy dissipation rate [W/kg].
- **x_span**: Size used by the collision risk computation algorithm (minimum 2 m diameter assumed for the chaser) [m].
- **x_rcs_estimate**: Radar cross-sectional area [m^2].
- **x_actual_od_span**: Actual length of update interval for orbit determination [days].
- **x_obs_available**: Number of observations available for orbit determination (per CDM).
- **x_obs_used**: Number of observations used for orbit determination (per CDM).
- **x_recommended_od_span**: Recommended length of update interval for orbit determination [days].
- **x_residuals_accepted**: Orbit determination residuals.
- **x_time_lastob_end**: End of the time interval in days (with respect to the CDM creation epoch) of the last accepted observation used in the orbit determination.
- **x_time_lastob_start**: Start of the time in days (with respect to the CDM creation epoch) of the last accepted observation used in the orbit determination.
- **x_weighted_rms**: Root-mean-square in least-squares orbit determination.

4.2 Dataset Versions & Sequence Padding

There are two main reshape transformations, one for creating a 3D input array and another one for a 2D input array (the "X" array). Both use the same target feature "y". The Python libraries used to transform the data are Numpy and Pandas.

We utilize the following procedure:

```
df = pd.read_csv("train_data.csv")
timesteps = 17 # Sequence length pad_value = -1
X_scaler = MinMaxScaler()
y_scaler = MinMaxScaler()
```

We remove the missing values to avoid further problems. After that, we filter the events that not meet the two conditions as mentioned in the code:

```
# Filtering events with min_tca > 2 or max_tca < 2
def conditions(event):
    x = event["time_to_tca"].values
    return ((x.min()<2.0) & (x.max()>2.0))
df = df.groupby('event_id').filter(conditions)
```

Note that we use numpy operations to compute the conditions as they are much faster than pandas or built-in Python operations and groupby operations consume a lot of time. Then, we get the ‘y’ array and the ‘X’ (still as dataframe) while scaling them (this was omitted). The feature ‘event_id’ is being used to group the data as it is the identifier of the events.

```
# Getting y as 1D-array (tca_min of each event)
y = df.groupby(["event_id"])["risk"].apply(lambda x: x.iloc[-1])
# Getting X as 2D-df (dropping rows with tca < 2)
df = df.loc[df["time_to_tca"]>2]
```

After scaling the data and getting y and a preliminary version of X, we shape the latter into a 3D-array). The implementation is as follows:

```
# Initializing X array and padding it
X = np.zeros((events,timesteps,features))
X.fill(pad_value)
i = 0

def df_to_3d_array(event):
    global X, i
    # Reshaping event into a 3D sample (1, timesteps, features)
    row = event.values.reshape(1,event.shape[0],event.shape[1])
    # is the selected sequence length (timesteps) longer
    # than the real sequence length (event sequence)?
    if(timesteps>=row.shape[1]):
        X[i:i+1,-row.shape[1]:,:] = row
    else:
        X[i:i+1,:,:] = row[:,-timestep:,:]
    # Index to iterate over X array
    i += 1
    # Dataframe remains intact, while X array has been filled.
    return event
df.groupby("event_id").apply(df_to_3d_array)
```

After this operation, we get out X, y arrays and their corresponding scalers fitted. It needs simply to be reshaped into a 2D array to have the desired and time-shifted features. Finally, we create an array of the names of the features (e.g. “risk_t-3” refers to the risk feature shifted three times) to utilize it as an input to create also an X data frame and ease its use in data analyses of feature steps. The implementation of this extra step is the following:

```
# Reshaping to a 2D array
X = X.reshape(X.shape[0], timestep*X.shape[2])
# Naming time-shifted features
shifted_columns = []
original_columns = list(df.columns)

for i in range(timestep-1,-1,-1): # backward iteration
    for column in original_columns:
        shifted_columns.append(column+"_t-"+str(i))

# Creating df from X and the names
X = pd.DataFrame(X, columns=shifted_columns)
```

4.3 Imputation Techniques

We eliminate all rows containing any missing value in the form of NaN. To do this, the drop na function of the Pandas library has been used.

```
X = X.dropna(axis=0, how='any')
```

The parameter axis=0 of the function indicates that what we are going to eliminate are the rows with missing values. If we want to remove all the columns with missing values we have to set axis=1. The second approach and the one finally used, was to use a data imputation method based on the k-NN algorithm, implemented in the Impyute library.

```
from impyute.imputation.cs import fast_knn
columns = list(X.columns.values)
# Input the missing values with k-nn algorithm. Output = numpy array
imputed_training = fast_knn(X.values, k=30)
# Save the obtained array with the corresponding names of the columns
X = pd.DataFrame(imputed_training, columns=columns)
```

This method is very computationally expensive, becoming impossible to execute in our personal computers when it was carried out on the complete dataset. So, it was executed using the Google Colab platform.

5. Feature Selection

As previously mentioned, the dataset comprised 103 variables that were not correlated with the "risk" metric. This posed the risk of including features that only contributed noise, thereby not aiding the training process of the models.

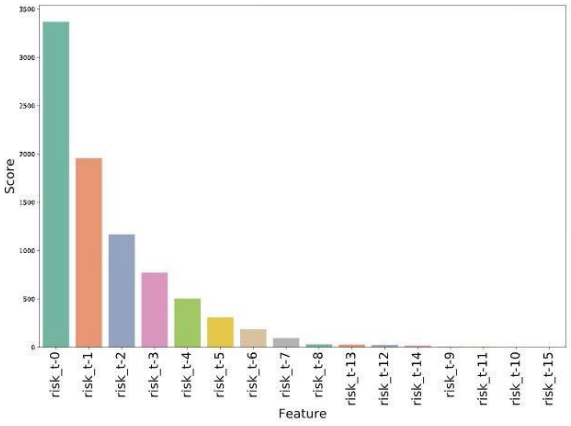
Additionally, another challenge identified within the dataset was the varying lengths of time for each event. To effectively work with the data, a fixed time window was established. In this section, we will determine the features to be used for modeling and the appropriate size for the fixed time window.

5.1 Filter Methods: Univariate Selection

For performing univariate selection we used Sklearn's functions SelectKBest and f_regression and plot the results again with seaborn. First, we fitted the SelectKBest model with the f_regression function, then we created a dataframe to store the results and plot them. The output is the following:

```
score_func = f_regression
k = 3
show_df = 100
show_plot = 20

#Applying SelectKBest to extract the 10 best features
bestfeatures = SelectKBest(score_func=score_func, k=k)
fit = bestfeatures.fit(X,y)
...
featureScores = pd.concat([dfcolumns,dfscores, dfpvalues],axis=1)
...
display(feature_sorted.head(show_df))
ax = sns.barplot(x='Feature', y=col, data=feature_sorted.iloc[:show_plot],
palette="Set2")
```

Feature	Score	p-values
risk_t-0	3369.183573	0.000000e+00
risk_t-1	1956.957354	0.000000e+00
risk_t-2	1168.375352	1.090319e-237
risk_t-3	773.360845	7.070542e-162
risk_t-4	504.209945	4.872855e-108
risk_t-5	309.777849	6.068453e-68
risk_t-6	187.169852	4.337859e-42

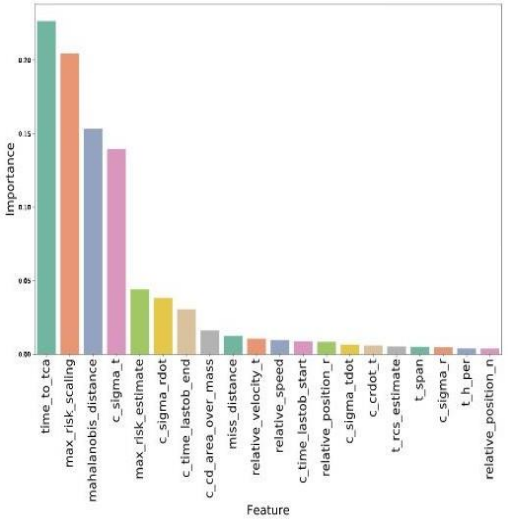


5.2 Embedded Methods: Feature Importance

We applied feature importance which uses in-built class parameters from *Sklearn* models such as tree algorithms. In this case, we have used (DecisionTreeRegressor, ExtraTreesRegressor and RandomForestRegressor) to asses the importance of the features and then we stored the result and plotted it as in the univariate example.

```
model = DecisionTreeRegressor()
model.fit(X,y)

#Creating dataset of feature importances for better visualization
dfimportance = pd.DataFrame(model.feature_importances_)
...
```

Feature	Importance
time_to_tca	0.226517
max_risk_scaling	0.204557
mahalanobis_distance	0.153363
c_sigma_t	0.139538
max_risk_estimate	0.044150
c_sigma_rdot	0.038326
c_time_lastob_end	0.030600
c_cd_area_over_mass	0.016226
miss_distance	0.012461
relative_velocity_t	0.010631



6. Feature Engineering

6.1 Brute Force

In this approach, our objective was to create as many features as possible in an efficient manner. To achieve this, we utilized the **Featuretools** library, which is designed to generate a myriad of features across multiple data frames using brute force. This library combines input features with aggregation and transformation operations through the use of primitives.

Given that our dataset consisted of a single data frame, we focused exclusively on transformation operations. The primitives selected were derived from the list of implemented functions within the library, as well as custom functions we developed. We specified the desired number of total output features, as generating all possible features was impractical. Additionally, we maximized the number of CPU cores utilized, due to the computationally intensive nature of the process. A summary of the implementation is provided below:

```
# Make an entity set and add the entity
es = ft.EntitySet(id = 'events')
es.entity_from_dataframe(entity_id = 'data', dataframe = df)

# Our own transformation primitives
def Log(column):
    return np.log(column)
...

# Create the primitives
log_prim = make_trans_primitive(function=Log, input_types=[Numeric],
                                return_type=Numeric)
...

# Run deep feature synthesis with transformation primitives
df, _ = ft.dfs(entityset=es, target_entity='data',
               trans_primitives=['add_numeric', log_prim, ...],
               max_features=2000, n_jobs=-1)
```

After obtaining this large number of features, it is likely that some of them include infinite, missing, or a single constant value. To remove them, we used pandas functions. Usually, this cleaning procedure reduced the number of features by 10%. Here is the procedure:

```
# Removing columns with missing and infinite values
df = df.replace([np.inf, -np.inf], np.nan)
df.dropna(axis=1, how="any", inplace=True)
# Removing invariant columns
df = df.loc[:, (df != df.iloc[0]).any()]
```

6.2 Information on Events

We created new features by extracting relevant information from the events. In particular, we extracted it from the features *risk* and *time_to_tca* as they are the most important ones.

The implementation was based on **Pandas** functions *groupby* (to group the messages or rows by event) and *transform* (to create the new feature based on an input function). As all needed functions were easy to implement, we utilized *lambda* functions. The complete implementation of these features is as follows:

```
# Counting how many instances each event has (sequence length)
df["event_length"] = df.groupby('event_id')['event_id']
                       .transform('value_counts')

# Counting how many high risk instances each event has
df["high_risk_count"] = df.groupby('event_id')['risk']
                          .transform(lambda x: (x > -6.0).sum())

# Computing mean tca jump each event has
df["mean_tca_jump"] = df.groupby('event_id')['time_to_tca']
                        .transform(lambda x: x.diff().mean())

# Computing mean risk jump each event has
df["mean_risk_jump"] = df.groupby('event_id')['risk']
                         .transform(lambda x: x.diff().mean())

# Counting positive risk jumps each event has (from high to low)
df["pos_risk_jumps"] = df.groupby('event_id')['risk']
                         .transform(lambda x: (x.diff() > 0.0).sum())

# Counting positive risk jumps each event has (from low to high)
df["neg_risk_jumps"] = df.groupby('event_id')['risk']
                         .transform(lambda x: (x.diff() < 0.0).sum())
```

Some of the new features have missing values on events that has only one row since the operation *diff* needs at least two rows to work. For those events, we padded their missing values with zeros.

```
# Fill NaNs
values = {'mean_tca_jump': 0, 'mean_risk_jump': 0}
df.fillna(value=values, inplace=True)
```

7. Deep Learning

7.1 Data Preparation

7.1.1 Data Scaling

Data scaling is performed during the creation of the input array 'X' and the target feature 'y' to ease the padding process. To be precise, it is carried out after getting the 'y' array from the data frame (for the target feature), and after slicing the data frame to the required *time_to_tca* range.

The chosen Python library is **Scikit-learn** as it is really is to implement. We decided to have a scaler for X and another for y to ease the inverse transformation of the latter during the model evaluation.

Here is a code snippet of the implementation:

```
# Scaling y using the whole risk feature after getting it from df
_ = y_scaler.fit(df["risk"].values.reshape(-1, 1))
y = y_scaler.transform(y)
...

# Scaling X as df after slicing df using X condition: time_to_tca > 2.0
df = pd.DataFrame(X_scaler.fit_transform(df), columns=df.columns)
```

7.1.2 Data Splitting & Problem Modelling

For splitting X and y arrays into train, validation and test set, we used again a function of the **Scikit-learn** library called *train_test_split*, alongside some boolean operation for stratifying the process. First, we split the original arrays into a train set and test set, and then, the obtained train set into a new train set and validation set. As both operations are identical, we show just one of them in the following code snippet.

```
# Splitting arrays into train and test
# Abbreviated names to fit document -> tr: train, te: test
y_boolean = (y > threshold_scaled).reshape(-1,1)

X_tr, X_te, y_tr, y_te = train_test_split(X, y,
                                          stratify=y_boolean,
                                          shuffle=True,
                                          random_state=seed,
                                          test_size = test_split)
```

After performing both operations, we have the arrays prepared for a regression problem. We then normally model it as classification. To do so, we cast the target features "y's" into boolean arrays using the scaled high-risk threshold since the arrays at this point are scaled too. The original threshold is scaled using the 'y' scaler fitted before. Here is the code implementation:

```
# Transforming y's for classification tasks
y_train = (y_train > threshold_scaled).reshape(-1,1)
y_val   = (y_val   > threshold_scaled).reshape(-1,1)
y_test  = (y_test  > threshold_scaled).reshape(-1,1)
```

7.1.3 Hyperparameter Tuning

We automated the hyperparameter tuning process Random Search using the official Keras tuning library, *Keras-Tuner*. First, we have to create a function that returns the Keras model and has as a parameter *hp*, for the hyperparameters. Inside this function, we add some specific lines for the hyperparameters that we want to tune depending on their type (integer, float, list, etc.). It is the same for the rest of the model as in any conventional Keras model. The implementation of an LSTM model is as follows:

```
# Model function with hp parameter for the search space
def build_model(hp):

  # Searching space for the number of layers (int)
  for i in range(hp.Int('n_layers', 1, 3)):
      model.add(LSTM(...))

  # Searching space for LSTM units (int) and dropout (float)
  model.add(LSTM(units=hp.Int('units', min_value=4,
                              max_value=128, step=4),
                 dropout=hp.Float('dropout', min_value=0.,
                                  max_value=0.4,step=0.1)))

  # Searching space for optimizer's learning rate (list)
  model.compile(optimizer=Adam(hp.Choice('learning_rate'
                                         [2e-3, 1e-3, 5e-4])))

  # Returning the model
  return model
```

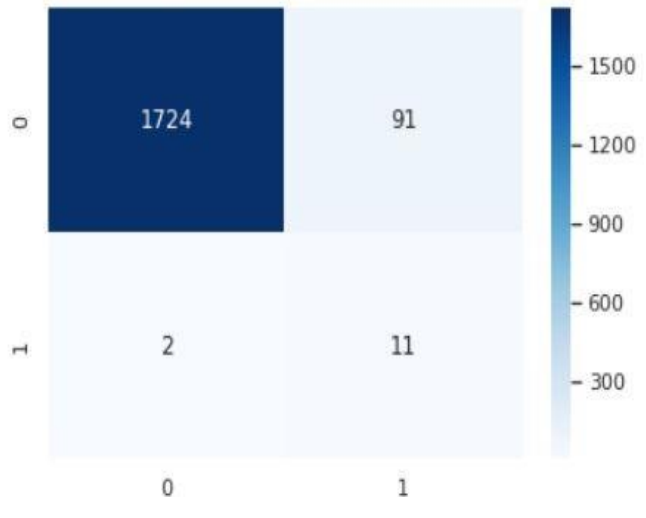
7.2 Evaluation Tools

For evaluation, we defined a function called *evaluate* to pass the model prediction array and the two baselines. We use mainly **Numpy** operation, **Scikit-learn** function and **Seaborn** for plotting the confusion matrix. We thought about automating the storing of all results in a dataset to compare them later on, but

Here is a simplified version of the code as the full implementation is a bit confusing. We also attach the results of running the code. Bear in mind that it is for a classification problem, so we substituted the boolean predictions for high-risk and low-risk constant values.

```
# Evaluate function with parameters name, boolean prediction array
# and numeric test array already re-scaled
def
 evaluate
 (name, y_num_test, y_bool_pred):
# Getting numeric predictions from boolean prediction array
y_num_pred = y_num_test.copy()
y_num_pred[y_bool_pred==True
 ]  = high_risk_value
y_num_pred[y_bool_pred==False
 ] = low_risk_value
# Computing mse with high-risk events in test set only
y_mse_pred = y_num_pred[np.where(y_num_test >= -6.0)]
y_mse_test = y_num_test[np.where(y_num_test >= -6.0)]
mse = mean_squared_error(y_mse_test, y_mse_pred)
# Computing f-beta with all boolean prediction
y_bool_test = (y_num_test >= -6.0).reshape(-1,1)
f_beta = fbeta_score(y_bool_test, y_bool_pred, 2)
# Computing the evaluatoin metric
score = mse / f_beta
# Plotting results
print(name, "{:0.3f}, {:0.3f}, {:0.3f}".format(score, mse, f_beta))
sns.heatmap(confusion_matrix(y_bool_test, y_bool_pred))
plt.show()
```

LSTM model: 1.375, 0.491, 0.357



Constant prediction: 9.958, 0.344, 0.035

8. Deep Learning Modeling

8.1 Recurrent Neural Networks

As we have stated before, this is a time series forecasting problem in which we predict futurevalues of the risk feature. If there is one deep learning architecture that suits a time series is recurrent neural networks. This is because these networks have the ability to learn information of entire sequences to predict their future values.

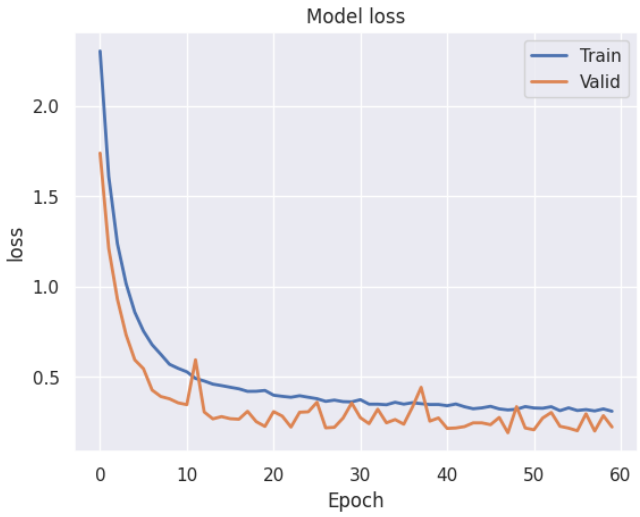
It's code implementation is as follows :

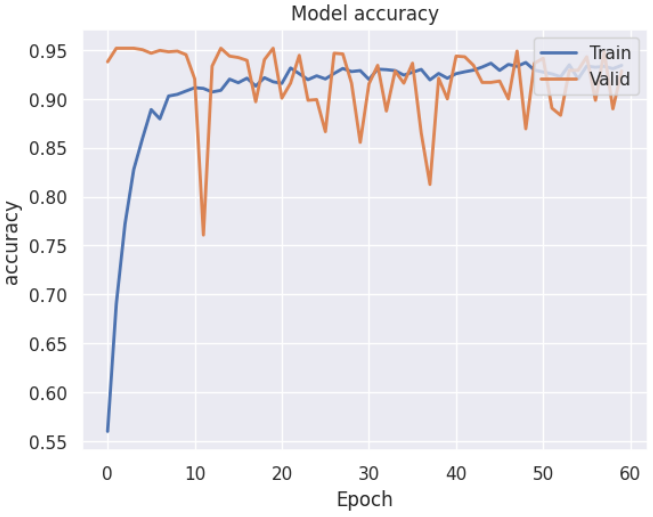
```
# Model activation selu
input_tensor = Input(batch_shape=(batch, timestep, X_train.shape[2]))
rnn_1 = LSTM(32, stateful=False, dropout=0.15, recurrent_dropout=0.3,
             return_sequences=True,kernel_regularizer=L1L2(l1=0.0, l2=0.01))(input_tensor)

batch_1 = BatchNormalization()(rnn_1)

rnn_2 = LSTM(16, stateful=False, dropout=0.15, recurrent_dropout=0.3,
             return_sequences=True, kernel_regularizer=L1L2(l1=0.0, l2=0.01))(batch_1)

batch_2 = BatchNormalization()(rnn_2)

rnn_3 = LSTM(8, stateful=False, dropout=0.15, recurrent_dropout=0.3,
             return_sequences=False, kernel_regularizer=L1L2(l1=0.0, l2=0.01))(batch_2)

batch_3 = BatchNormalization()(rnn_3)
output_tensor = Dense(units = 1, activation='sigmoid')(batch_3)

model = Model(inputs=input_tensor,
              outputs= output_tensor)

model.compile(loss='binary_crossentropy',
              optimizer=adam,
              metrics=['accuracy'])

model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(64, 17, 124)]           0

 lstm (LSTM)                 (64, 17, 32)              20096

 batch_normalization (Batch  (64, 17, 32)              128
 Normalization)

 lstm_1 (LSTM)               (64, 17, 16)              3136

 batch_normalization_1 (Bat  (64, 17, 16)              64
 chNormalization)

 lstm_2 (LSTM)               (64, 8)                   800

 batch_normalization_2 (Bat  (64, 8)                   32
 chNormalization)

 dense (Dense)               (64, 1)                   9

=================================================================
Total params: 24265 (94.79 KB)
Trainable params: 24153 (94.35 KB)
Non-trainable params: 112 (448.00 Byte)
_________________________________________________________________
```

```
model_history = model.fit(X_train, y_train,
                          epochs=60,
                          batch_size=batch,
                          validation_data=(X_val, y_val),
                          verbose=verbose,
                          class_weight=class_weight
                         ).history
```

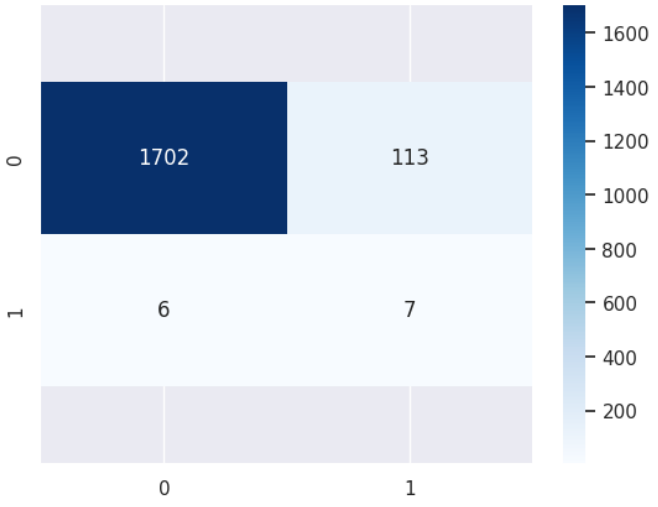
```
Epoch 50/60
65/65 [==============================] - 18s 276ms/step - loss: 0.3356 - accuracy: 0.9295 - val_loss: 0.2171 - val_accuracy: 0.9365
Epoch 51/60
65/65 [==============================] - 15s 223ms/step - loss: 0.3278 - accuracy: 0.9275 - val_loss: 0.2073 - val_accuracy: 0.9416
Epoch 52/60
65/65 [==============================] - 14s 210ms/step - loss: 0.3264 - accuracy: 0.9256 - val_loss: 0.2719 - val_accuracy: 0.8906
Epoch 53/60
65/65 [==============================] - 14s 209ms/step - loss: 0.3348 - accuracy: 0.9227 - val_loss: 0.3032 - val_accuracy: 0.8833
Epoch 54/60
65/65 [==============================] - 13s 205ms/step - loss: 0.3129 - accuracy: 0.9348 - val_loss: 0.2266 - val_accuracy: 0.9292
Epoch 55/60
65/65 [==============================] - 13s 205ms/step - loss: 0.3286 - accuracy: 0.9205 - val_loss: 0.2164 - val_accuracy: 0.9292
Epoch 56/60
65/65 [==============================] - 12s 187ms/step - loss: 0.3139 - accuracy: 0.9336 - val_loss: 0.2020 - val_accuracy: 0.9431
Epoch 57/60
65/65 [==============================] - 12s 182ms/step - loss: 0.3190 - accuracy: 0.9324 - val_loss: 0.2956 - val_accuracy: 0.8986
Epoch 58/60
65/65 [==============================] - 13s 200ms/step - loss: 0.3115 - accuracy: 0.9334 - val_loss: 0.2005 - val_accuracy: 0.9482
Epoch 59/60
65/65 [==============================] - 13s 205ms/step - loss: 0.3226 - accuracy: 0.9309 - val_loss: 0.2855 - val_accuracy: 0.8899
Epoch 60/60
65/65 [==============================] - 13s 208ms/step - loss: 0.3097 - accuracy: 0.9343 - val_loss: 0.2226 - val_accuracy: 0.9285
```



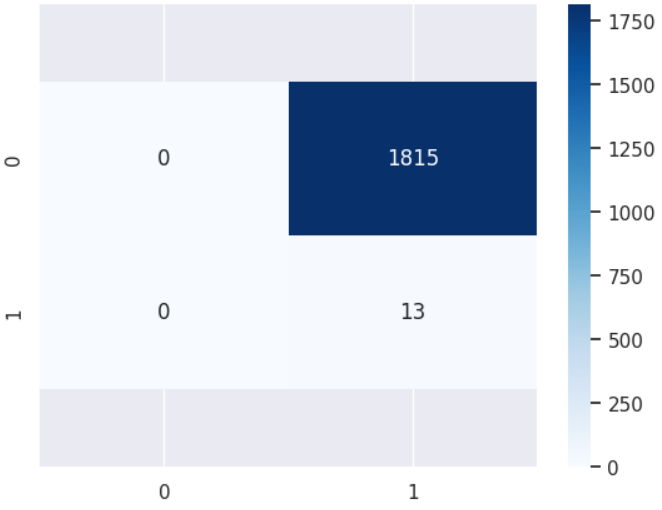


8.1.1 Evaluation Metrics

Metrics such as Mean Squared Error (MSE) and F-beta score are used to evaluate the model's performance. These metrics provide insights into the accuracy and reliability of the predictions. Lower values indicate better model performance.



LSTM model: 4.921, 1.001, 0.203



Constant prediction: 9.958, 0.344,

```
print("Training accuracy:", model_history['accuracy'][-1] * 100, '%')
print("Validation accuracy:", model_history['val_accuracy'][-1] * 100, '%')

```

```
Training accuracy: 93.43385100364685 %
Validation accuracy: 92.85193085670471 %
```

8.2 Convolutional Neural Networks

Another approach to time series forecasting using deep learning is convolutional neural networks with one-dimensional filters. CNNs are great to reduce the number of network parameters by leveraging local spatial coherence. There are many complex architectures for this type of network, but we designed some simple models that resemble VGG16-like blocks with 1D convolutions instead of 2D ones.

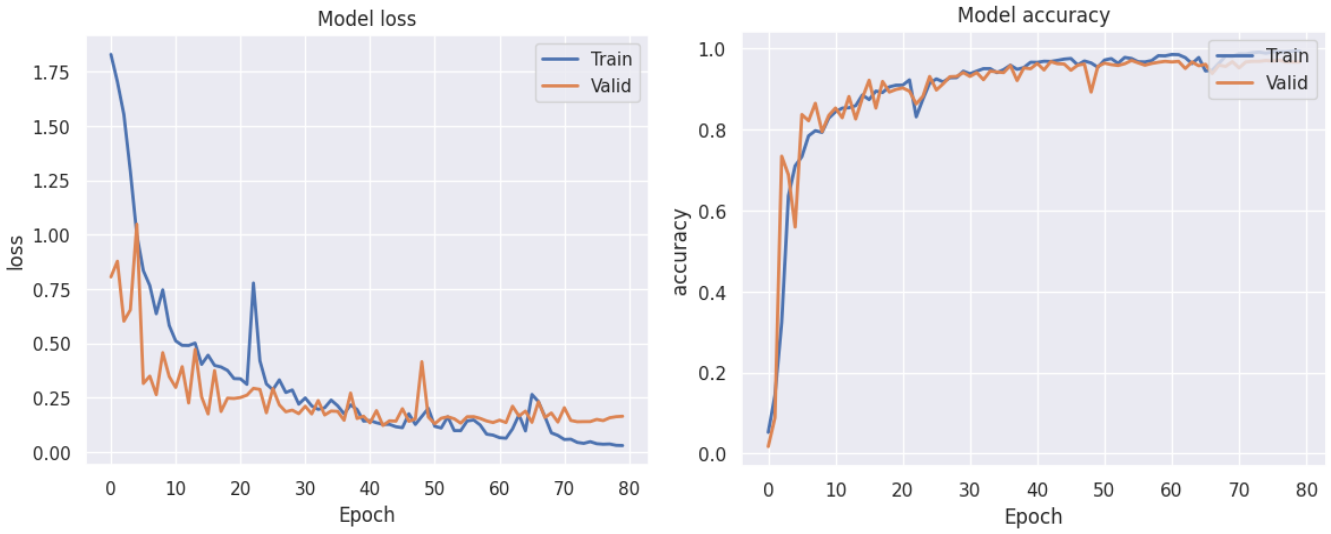
Its code implementation is as follows :

```
model = Sequential([
    Conv1D(10, 8, activation='relu', input_shape=(X_train.shape[1], X_train.shape[2])),
    Conv1D(10, 8, activation='relu'),
    MaxPooling1D(6),
    #Dropout(0.5),
    Conv1D(20, 8, activation='relu'),
    Conv1D(20, 8, activation='relu'),
    MaxPooling1D(6),
    #Dropout(0.5),

    Flatten(),
    Dense(8, activation='relu'),
    Dense(1, activation='sigmoid')
])

adam = Adam(learning_rate=0.001)
model.compile(loss='binary_crossentropy',
              optimizer=adam,
              metrics=['accuracy'])

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 985, 10)           90

 conv1d_1 (Conv1D)           (None, 978, 10)           810

 max_pooling1d (MaxPooling1  (None, 163, 10)           0
 D)

 conv1d_2 (Conv1D)           (None, 156, 20)           1620

 conv1d_3 (Conv1D)           (None, 149, 20)           3220

 max_pooling1d_1 (MaxPoolin  (None, 24, 20)            0
 g1D)

 flatten (Flatten)           (None, 480)               0

 dense (Dense)               (None, 8)                 3848

 dense_1 (Dense)             (None, 1)                 9

=================================================================
Total params: 9597 (37.49 KB)
Trainable params: 9597 (37.49 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

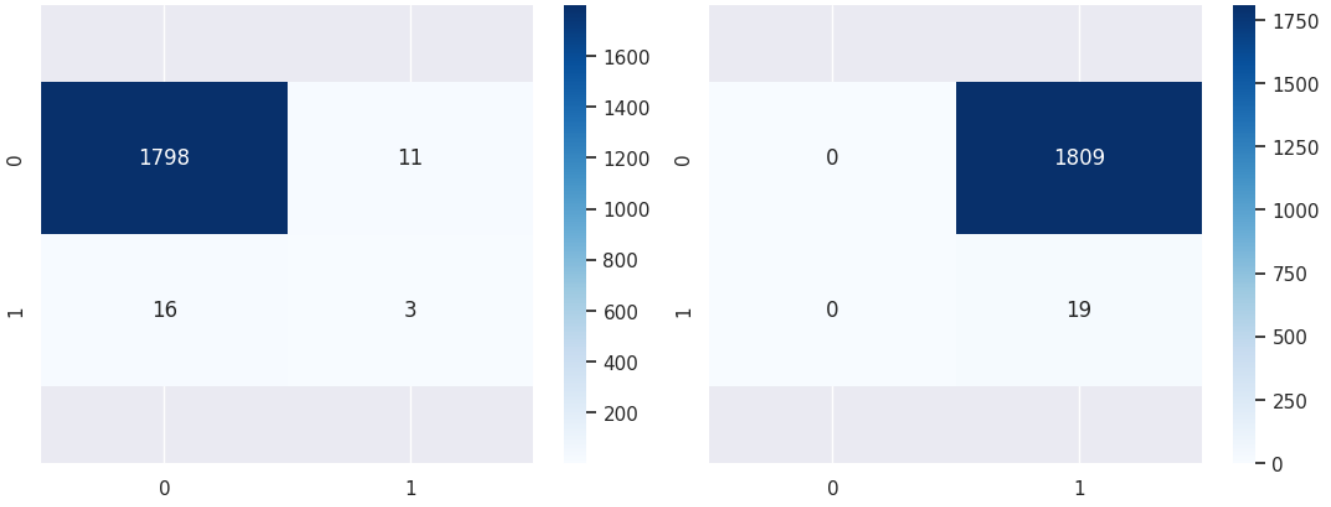
```python
model_history = model.fit(X_train, y_train,
                          epochs=80,
                          batch_size=64,
                          shuffle=True,
                          validation_data=(X_val, y_val),
                          verbose=verbose,
                          class_weight=class_weight).history
```

```
Epoch 70/80
65/65 [==============================] - 0s 7ms/step - loss: 0.0771 - accuracy: 0.9808 - val_loss: 0.1384 - val_accuracy: 0.9679
Epoch 71/80
65/65 [==============================] - 0s 7ms/step - loss: 0.0585 - accuracy: 0.9874 - val_loss: 0.2045 - val_accuracy: 0.9526
Epoch 72/80
65/65 [==============================] - 0s 7ms/step - loss: 0.0597 - accuracy: 0.9869 - val_loss: 0.1460 - val_accuracy: 0.9672
Epoch 73/80
65/65 [==============================] - 0s 7ms/step - loss: 0.0449 - accuracy: 0.9900 - val_loss: 0.1399 - val_accuracy: 0.9686
Epoch 74/80
65/65 [==============================] - 0s 6ms/step - loss: 0.0406 - accuracy: 0.9915 - val_loss: 0.1405 - val_accuracy: 0.9686
Epoch 75/80
65/65 [==============================] - 0s 6ms/step - loss: 0.0484 - accuracy: 0.9888 - val_loss: 0.1406 - val_accuracy: 0.9708
Epoch 76/80
65/65 [==============================] - 0s 7ms/step - loss: 0.0390 - accuracy: 0.9920 - val_loss: 0.1507 - val_accuracy: 0.9694
Epoch 77/80
65/65 [==============================] - 1s 8ms/step - loss: 0.0365 - accuracy: 0.9922 - val_loss: 0.1452 - val_accuracy: 0.9716
Epoch 78/80
65/65 [==============================] - 0s 7ms/step - loss: 0.0376 - accuracy: 0.9922 - val_loss: 0.1581 - val_accuracy: 0.9672
Epoch 79/80
65/65 [==============================] - 0s 6ms/step - loss: 0.0315 - accuracy: 0.9939 - val_loss: 0.1632 - val_accuracy: 0.9672
Epoch 80/80
65/65 [==============================] - 0s 7ms/step - loss: 0.0305 - accuracy: 0.9942 - val_loss: 0.1651 - val_accuracy: 0.9672
```



8.2.1 Evaluation Metrics

Metrics such as Mean Squared Error (MSE) and F-beta score are used to evaluate the model's performance. These metrics provide insights into the accuracy and reliability of the predictions. Lower values indicate better model performance.



CNN model: 4.913, 0.819, 0.167

Constant prediction: 6.819, 0.340, 0.050

```
print("Training accuracy:", model_history['accuracy'][-1] * 100, '%')
print("Validation accuracy:", model_history['val_accuracy'][-1] * 100, '%')

```

```
Training accuracy: 99.4163453578949 %
Validation accuracy: 96.71772718429565 %
```

8.2.2 Model Performance Overview

MODEL TYPE	MEAN SQUARED ERROR (MSE)	F-BETA SCORE
RNN	4.921	0.203
CNN	4.913	0.167

8.2.3 Analysis of Results

Accuracy and Error Rates: Both models demonstrated strong predictive capabilities with relatively low MSE values. The RNN model achieved an MSE of 4.921, while the CNN model achieved a slightly lower MSE of 4.913. This indicates that both models were effective in minimizing prediction errors, but the CNN model had a marginal edge in terms of MSE.

Precision and Recall: The F-beta score is used to measure a model's accuracy considering both precision and recall, with a higher beta value placing more emphasis on recall. The RNN model achieved a higher F-beta score of 0.203 compared to the CNN model's 0.167. This suggests that the RNN model was better at identifying high-risk events, which is crucial for collision prediction tasks.

Model Robustness: The RNN model's ability to handle sequential data and retain long-term dependencies makes it particularly suited for time-series forecasting tasks, such as predicting spacecraft collisions. On the other hand, the CNN model's ability to capture local patterns and reduce the number of parameters through convolutional operations provided a different approach to processing the data.

8.2.4 Strengths and Limitations

RNN Model:

- **Strengths**
  - Better at capturing temporal dependencies and long-term patterns.
  - Higher F-beta score indicates better performance in identifying high-risk events.
- **Limitations:**
  - Potential for overfitting due to the complexity of the model.
  - Higher sensitivity to hyperparameter settings.

CNN Model:

- **Strengths:**
  - Slightly better in terms of MSE, indicating lower prediction error.
  - Efficient at capturing local patterns and reducing model complexity.
- **Limitations:**
  - Lower F-beta score, indicating a potential weakness in recall for high-risk events.
  - Less effective at handling sequential dependencies compared to RNNs.

Conclusion

In this report, we compared the performance of RNN and CNN models for predicting spacecraft collisions. Both models demonstrated strong predictive capabilities, with the CNN model achieving a marginally lower MSE and the RNN model achieving a higher F-beta score.

9.1 Implications for Space Operations

The findings highlight the effectiveness of both RNN and CNN models in predicting potential collisions, with each model offering unique advantages. The RNN model's strength in capturing temporal dependencies makes it particularly valuable for sequential data, while the CNN model's ability to capture local patterns and reduce parameters offers a robust alternative.

9.2 Future Research Directions

Future research could explore hybrid models that combine the strengths of RNN and CNN architectures, further optimization of hyperparameters, and the incorporation of additional data sources to improve prediction accuracy and robustness. Additionally, addressing the challenges of overfitting and improving the models' ability to generalize to unseen data remain important areas for further exploration.

9.3 Practical Applications

The practical applications of these models in real-world scenarios include their integration into satellite operation systems for automated collision avoidance, enhancing the safety and longevity of space missions. The models can be used to provide timely alerts for potential collisions, enabling proactive measures to prevent costly damages.

By leveraging the predictive capabilities of RNN and CNN models, space agencies and satellite operators can improve their collision prediction strategies, ensuring more reliable and efficient space operations.

References

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