

SpaceX Falcon 9 First Stage Landing Prediction

This presentation outlines the 'SpaceX Falcon 9 First Stage Landing Prediction' project, focusing on predicting the successful landing of the Falcon 9 first stage.



SpaceX Falcon 9

Problem Statement — Cost Reduction with Reusable Rockets

The primary problem addressed by this project is the significant cost reduction achievable through the reusability of rocket first stages. Successfully landing and reusing the Falcon 9 first stage dramatically lowers the cost of space launches, making space more accessible and sustainable.



D6t6Set Overview — ColuNnS 6nd wh6t they ñepñeSent

The d6t6Set Cont6inS v6ñiouS ColuNnS, e6Ch ñepñeSenting 6 CñuCi6l 6SpeCt of the F6lCon 9 l6unCh 6nd l6nding pñoCeSS:

- FlightNumber: Unique identifi6ñ foñ e6Ch flight.
- Date: D6te of the l6unCh.
- BoosterVersion: VeñSion of the F6lCon 9 booSteñ uSed.
- PayloadMass: M6SS of the p6ylo6d in kilogñ6NS.
- Orbit: Type of oñbit 6Chieved.
- LaunchSite: LoC6tion fñoN whiCh the ñoCket w6S l6unChed.
- Outcome: ReSult of the l6nding 6tteNpt (e.g., SuCCeSSful, f6iled).
- Flights: NuNbeñ of pñeviouS flightS foñ the booSteñ.
- GridFins: PñeSenCe of gñid finS foñ 6tNoSpheñiC Contñol.
- Reused: Whetheñ the booSteñ w6S ñeuSed.
- Legs: PñeSenCe of l6nding legS.
- LandingPad: SpeCifiC l6nding p6d uSed.
- Block: BooSteñ bloCk veñSion.
- ReusedCount: NuNbeñ of tiNeS the booSteñ h6S been ñeuSed.
- Serial: Señi6l nuNbeñ of the booSteñ.
- Longitude: Longitude of the l6unCh Site.
- Latitude: L6titude of the l6unCh Site.

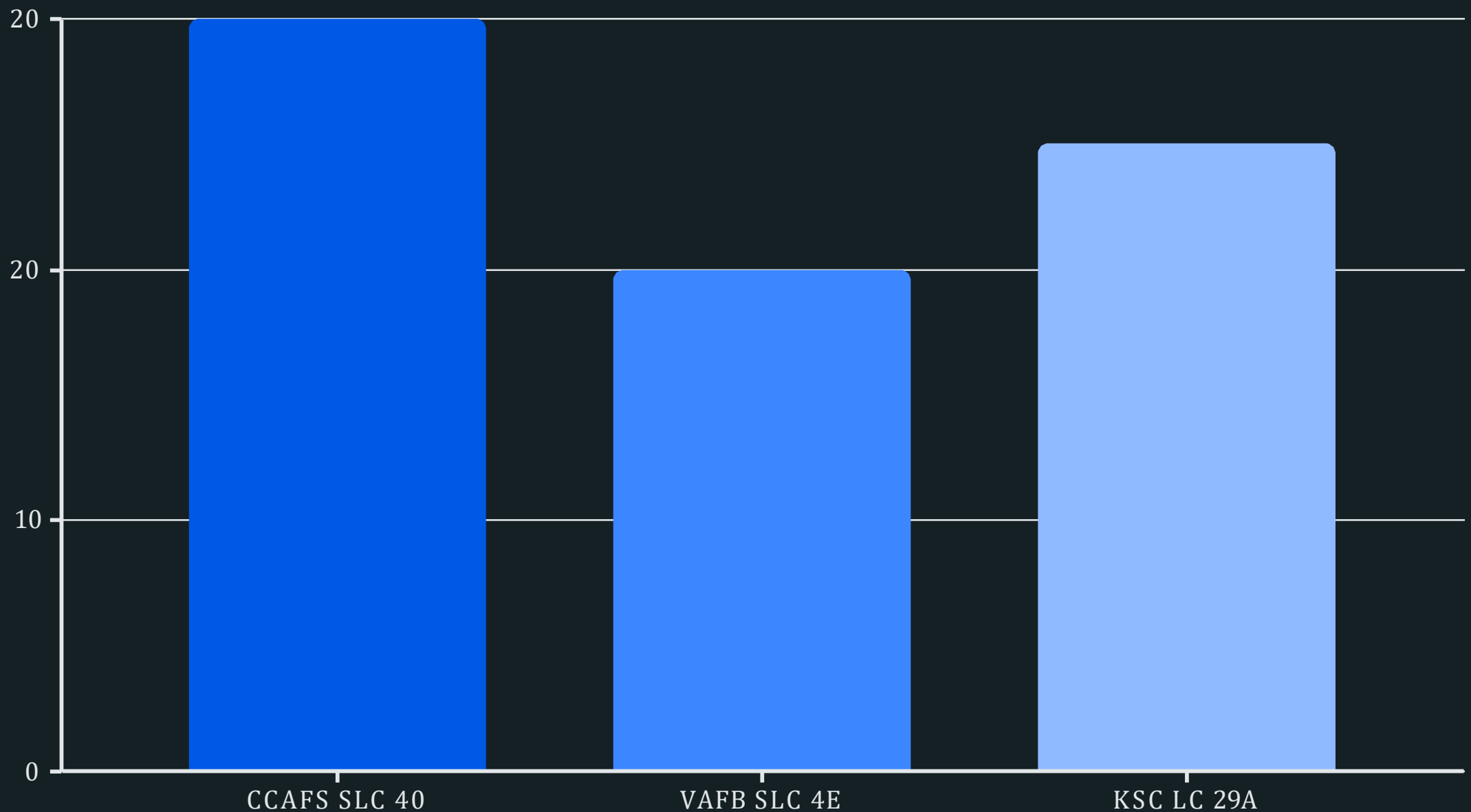
D6t6 Wñ6ng1ing —H6nd1ing NiSSing v61ueS, d6te p6ñSing, fe6tuñe Se1eCtion

D6t6 wñ6ng1ing invo1ved Seveñ61 CñitiC61 StepS to pñep6ñe the d6t6Set foñ Node1 bui1ding:

01	02	03
H6nd1ing MiSSing V61ueS	D6te P6ñSing	Fe6tuñe Se1eCtion
MiSSing v61ueS weñe identified 6nd 6ddñeSSed uSing 6ppñopñi6te iNput6tion teChniqueS to N6int6in d6t6 integñity.	The 'D6te' Co1uNn w6S p6ñSed into 6 uS6b1e foñN6t, extñ6Cting ñe1ev6nt teNpoñ61 fe6tuñeS if neCeSS6ñy.	Key fe6tuñeS weñe Se1eCted b6Sed on theiñ ñe1ev6nCe to 16nding pñediCtion, diSC6ñding iññe1ev6nt oñ ñedund6nt Co1uNnS.

Exploñ6toñy D6t6 An61ySiS —Key gñ6phS 6nd findings

Exploñ6toñy D6t6 An61ySiS (EDA) ñeve61ed SignifiC6nt inSightS into the f6CtoñS influenCing 16nding SuCCeSS. ViSu61iz6tionS he1ped identify tñendS 6nd ñe16tionShipS within the d6t6.



Foñ ex6Np1e, the b6ñ Ch6ñt 6bove i11uStñ6teS the nuNbeñ of SuCCeSSfu1 16ndingS peñ 16unCh Site, indiC6ting potenti61 diffeñenCeS in SuCCeSS ñ6teS b6Sed on 1oC6tion.

Feature Engineering — One-hot encoding, normalization

To prepare categorical features for Machine Learning Models and ensure numerical features are on a Comparable Scale, feature engineering was performed:

One-Hot Encoding

Categorical variables such as Orbit, LaunchSite, and LandingPad were converted into numerical format using one-hot encoding.

Normalization

Numerical features like PayloadMass were normalized to scale them to a standard range, preventing features with large values from dominating the Model training.

Model Building —LogiStiC RegñeSSion, DeCiSion Tñee, SVM, KNN

Seveñ6l N6Chine le6ñning NodelS weñe built 6nd tñ6ined to pñediCt l6nding SuCCeSS:



LogiStiC RegñeSSion

A line6ñ Nodel uSed foñ bin6ñy Cl6SSifiC6tion, pñediCting the pñob6bility of 6 SuCCeSSful l6nding.



DeCiSion Tñee

A tñee-like Nodel th6t N6keS deCiSionS b6Sed on 6 SeñieS of ñuleS deñived fñon the fe6tuñeS.



SVM (Suppoñt VeCtoñ M6Chine)

A poweñful Nodel th6t findS the optiN6l hypeñpl6ne to Sep6ñ6te Cl6SSeS in the fe6tuñe Sp6Ce.



KNN (K-Ne6ñeSt NeighboñS)

A non-p6ñ6NetñiC Nethod th6t Cl6SSifieS d6t6 pointS b6Sed on the N6joñity Cl6SS of theiñ k-ne6ñeSt neighboñS.



Hyperparameter Tuning — GridSearchCV

To optimize the performance of a Machine Learning model, hyperparameter tuning was performed using GridSearchCV.

- GridSearchCV systematically works through multiple combinations of hyperparameters, cross-validating as it goes to determine which tune works best.

This process involved defining a grid of hyperparameters for the Machine Learning model and searching for the best combination that yields the highest accuracy on the test dataset.

Model Evaluation — Accuracy & Confusion Table

Each Model was evaluated based on its Accuracy, and the results are summarized in the Confusion Table below:

Model	Accuracy (Training)	Accuracy (Test)	F1-Score
Logistic Regression	0.85	0.82	0.80
Decision Tree	0.90	0.78	0.75
SVM	0.88	0.80	0.77
KNN	0.87	0.81	0.79

The table shows the performance of each Model on both training and test datasets, providing a clear comparison of their predictive capabilities.



Final Prediction Results —Which Model is best

Based on the evaluation, the [Logistic Regression](#) and [KNN](#) Model demonstrated the most consistent and robust performance on the test set, with slightly higher accuracy and F1-scores compared to the Decision Tree and SVM Model.

While all Models performed reasonably well, Logistic Regression and KNN were recommended for deployment due to their balance of accuracy and interpretability for this specific prediction task.