Comparison of Machine Learning Models for Predicting the Impact of Acquisitions on Innovation in the Defense Sector

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Dedication

The author wishes to dedicate this research to his wife and son. Their sacrifices and support throughout school made everything possible. I would also like to thank my parents, who instilled a lifelong love of learning.

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The author wishes to thank my advisor, Dr. Rebecca Yassan, for sharing her expertise in the development of this praxis. I would also like to thank Dr. Blackford and Dr. Fossaceca whose courses, Uncertainty Analysis and Machine Learning, formed the basis for the analysis used in this praxis.

Abstract of Praxis

Comparison of Machine Learning Models for Predicting the Impact of Startup Acquisitions on Innovation in the Defense Sector

With the Department of Defense identifying innovation as a key enabler for maintaining military superiority, the defense industry has made increasing this capability a priority. Defense companies have participated in mergers and acquisitions to augment internal research and development to meet the Department of Defense's goals. Selecting acquisitions that will increase innovation is a challenging task for defense companies as wrong acquisitions can decrease the acquiring company's ability to innovate.

This praxis employed the patent success ratio as a metric for measuring innovation, and then used different machine learning techniques to predict changes to Patent Success Ratio resulting from acquisitions at 3- and 5-year periods after acquisition. Those models were then compared across several metrics. The research resulted in models that were able to predict with more than 75% accuracy the effect on Patent Success Ratio for the 3-year period after acquisition and over 80% for and 5-year periods post-acquisition performance. These tools will enable decision makers in the defense industry to make informed decisions when selecting acquisitions to increase innovation. Additionally, the praxis shows that acquisition count alone is not an indicator of increased innovation. Results show that ensemble models using several different techniques provide the best prediction of innovation improvement for defense companies.

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List of Symbols

A	Number of patent applications without being granted
G	The number of patents granted
d	Time period for PSR
F1	F1 score
FN	Number of false negatives
FP	Number of false positives
FPR	False positive rate
NPSR	Normalized PSR
NPV	Negative predictive value
PPV	Positive predictive value
PSR	Patent Success Ratio PSR
*PSR**	PSR for all patents in a given time period
TN	Number of true negatives
TP	Number of true positives
TPR	True positive rate
Y	Acquisition Year

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List of Acronyms

AWS	Amazon Web Services
ANN	Artificial neural networks
AUC	Area Under Curve
DSS	Design Science Studio
DoD	Department of Defense
FN	False Negative
FP	False Positive
FPR	False Positive Rate
GDP	Gross Domestic Product
KNN	K-Nearest Neighbors
LBFGS	L-memory Broyden–Fletcher–Goldfarb–Shanno algorithm
M&A	Mergers and Acquisitions
ML	Machine Learning
NPV	Negative Predictive Value
PN	Predicted Negative
PPV	Positive Predictive Value
PP	Predicted Positive
PSR	Patent Success Ratio
R&D	Research and Development
ReLU	Rectified Linear Activation Function
ROC	Receiver Operating Characteristic
SIPRI	Stockholm International Peace Research Institute

SVM	Support Vector Machine
TN	True Negative
TP	True Positive
TPR	True Positive Rate
USPTO	US Patent and Trademark Office
VC	Venture Capital

List of Glossary of Terms

Assets	Money, materials, staff, and other resources that can be drawn on by a person or organization to function effectively
Acquirer	Defense company purchasing the startup
Discretionary budgets	Costs for business purchases that can be reduced or eliminated without impacting the business in the short term
Exit	For startups, an exit is the result of an IPO, acquisition by another company, or bankruptcy of a firm
Innovation	The development of new or improved products, processes, and services
Machine Learning	The use of algorithms that can analyze data using statistical methods without following explicit instructions user instructions
Open Innovation	The concept that an organization does not rely solely on their own internal knowledge exclusive of external sources of innovation
Patent Success Ratio	Measure of patent submittals to patent grants, a measure of innovation
R&D intensity	Ratio of research and development spend to sales
Startup	A company undertaken by an entrepreneur to seek, develop, and validate a scalable business model

Introduction

1.1 Background

With the United States (US) Department of Defense (DoD) pushing innovation as a key enabler for maintaining military superiority, innovation has been a critical priority for the defense industry (Bertuca, 2016). The DoD has expanded its defense contracting to traditional commercial vendors, such as Amazon Web Services (AWS) and Google's government cloud offerings. Additionally, they are working with new companies entering the defense sphere, such as Palantir Technologies, a data analytics technology company co-founded by PayPal's Peter Thiel (Chapman, 2020). The focus on innovation and working with commercial companies, considered more innovative (Amyx, 2020), force traditional defense companies to increase innovation to avoid lagging far behind the private sector.

Internal research and development (R&D) is a common driver of innovation and helps organizations to stay ahead of their competitors (Ma & Liu, 2017). R&D alone may not be enough to address companies' innovation needs; many companies have adopted mergers and acquisitions (M&A) to augment their internal R&D and innovation development. The acquisition of startups provides a faster path toward acquiring innovative technology instead of developing it internally (Cefis & Triguero, 2016). M&A help companies to keep up with the competition, including access to technology, markets, and customers (Carbone, 2011; Ma & Liu, 2016), with minimal risk and more efficient use of spending. This approach has become key for high-tech industries, including electronics, communications, and biotechnology, to improve market power and strengthen innovative performance (Yang et al., 2014).

Startups are a natural target for established companies to acquire technology since startups often include acquisitions in the end state of their business plans (Zhao et al., 2019). Although the idea behind using M&A is to accelerate innovation, doing so can place strain on the acquiring company, reducing its internal R&D spending (Zhao et al., 2019). Assimilating an acquired company and synergizing its people and processes require effort. These stresses on both the acquiring and acquired companies have the potential to offset any gains from the acquisition itself (Trichterborn et al., 2016).

Different techniques, such as machine learning (ML), have been proposed to measure innovation and determine how acquisitions affect it. ML provides companies, including those in the defense space, with the capability to analyze historical defense acquisition data to accurately select startup acquisitions that are likely to increase their innovation.

1.2 Research Motivation

With a narrow customer base, the US defense industry has driven a general consolidation within the industry to reduce competition and increase innovation (Mahoney, 2021; Reiss, 2021), resulting in the prevalence of large-scale M&A activities (Voth, 2021). Due to their lean discretionary budgets, defense companies must be as efficient as possible to remain competitive (Zhao et al., 2019). They need tools to make informed decisions on which acquisitions increase innovation and which to avoid. Limited research, exists on models and tools that can help defense companies make informed decisions and predict the outcomes of acquisitions on future innovation. This research, aims to provide defense contractors with the capabilities to be more successful in increasing innovation through acquisition.

1.3 Problem Statement

Defense companies that pursue external acquisitions to supplement internal R&D for new technological innovation redirect internal research funding and reduce innovation.

Defense companies participate in M&A to accelerate innovation and supplement internal R&D in order to acquire knowledge and new technology (Kim et al., 2022). An acquisition is not completely advantageous for the acquiring company as any technology or innovative capability gained through the acquisition may be partially or fully offset by reductions in internal R&D funding at the acquiring company, decrease productivity due to the acquisition's integration, and impact the acquired company's culture and workflow (Trichterborn et al., 2016). M&A activities have been shown to have a 44 to 50 percent failure rate (Das & Kapil, 2012).

1.4 Thesis Statement

An ML model using startup and acquirer attributes enables defense companies to select startups that will increase their innovation, as measured by the patent success ratio (PSR).

By analyzing defense companies' acquisitions of startups against their PSR values, this praxis determines which ML-based model can accurately predict outcomes of acquisitions on innovation within the defense sector. This model would offer defense companies a tool to evaluate acquisitions to increase innovation and determine whether their planned outcomes are achievable.

1.5 Research Objectives

This praxis has four main objectives:

1. To determine whether acquisitions alone will increase innovation, independent of other factors.
2. To find out whether publicly available information can be used to successfully train a model to predict innovation results of acquisitions.
3. To identify which of the tested ML models is most effective, using accuracy and area under curve (AUC) metrics, in predicting innovation impacts of acquisitions.
4. To determine whether ML models can be successful at making predictions at 3-year or 5-year timeframes.

1.6 Research Questions and Hypotheses

This praxis investigates the relationship between startups and acquiring companies to predict the acquiring companies' PSR after acquisition. The research questions are as follows:

RQ1: Does a relationship exist between startup acquisitions and an increased PSR at the acquiring defense company post acquisition?

RQ2: How accurate are models developed to estimate PSR changes using startup acquisition attributes based on accuracy and receiver operating characteristic (ROC)–Area Under Curve (AUC)?

The praxis examines different ML models that use the same variables to determine which model will best predict PSR changes. Accordingly, the following hypotheses are proposed:

H1: Startup acquisitions are associated with a statistically significant increase in the PSR of the acquiring company post acquisition.

H2: A naïve Bayes network can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.

H3: A decision tree model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.

H4: A support vector machine (SVM) model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.

H5: A K-nearest neighbor (KNN) model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.

H6: A neural network model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.

H7: A random forest model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.

H8: A boosting ML model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.

H9: An ensemble averaging model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.

1.7 Scope of Research

This praxis reviews available metrics to measure innovation within companies. Metrics that have the largest publicly available datasets were used to train ML models. Multiple techniques were tested to analyze the publicly available data for making predictions on which acquisitions resulted in increased innovation for acquiring companies. Standard regression analysis was performed to determine whether the relationship between acquisitions count and PSR is statistically significantly. More comprehensive ML techniques were employed to draw additional conclusions and make predictions of the PSR effects of acquisitions. These analyses were performed over two different time periods. The results show which ML techniques and models were most successful at making innovation predictions, and the time frames where those predictions were applicable. The successful ML models in this praxis can be used by defense companies to predict outcomes for acquisitions and to improve the success of acquisitions in terms of increased innovation. The same techniques can be tested against broader industries outside of defense, either directly or as a starting point for a more generic model.

1.8 Research Limitations

There are a few limitations to this praxis. First, the dataset for acquisitions was obtained from CrunchBase, a crowdsourced database. No central authority provided data verification, quality checks, or requirements for users to complete all data fields in the

database; some data had missing fields. Second, this dataset included only the largest US defense companies. Factors affecting startup acquisitions for small- and medium-sized defense companies may differ from those impacting larger ones.

Third, only publicly available data from either the U.S. Patent and Trademark Office or CrunchBase were used. Publicly available data do not account for internal elements, including project planning, the nature of leaders, processes, assets, and other non-publicly available factors that can affect the outcomes of acquisitions (Zhao et al., 2019). The praxis did not address any of these internal factors as the measure of innovation was tied to PSR.

Finally, no new ML models were developed for this praxis. Existent standard ML models were employed in this praxis: naïve Bayes, decision trees, SVM, KNN, artificial neural networks, random forests, boosting, and ensemble averaging model.

1.9 Organization of Praxis

The remainder of this praxis is organized as follows: Chapter 2 presents the literature review that provides a comprehensive overview of previous research on innovation, startups, M&A, and ML as they relate to each other. It also includes the history of these subjects in relation to the praxis topic. Chapter 3 covers the research methodology and explains the dataset used for analysis, the method of model development, and the approach to data analysis with respect to the praxis hypotheses. Chapter 4 addresses the research hypotheses and presents the results, as generated by the methodology of Chapter 3. Chapter 5 summarizes the results of the research, tying together all elements of the praxis, defining its contributions to the body of knowledge, and providing recommendations for future research.

Literature Review

2.1 Introduction

This chapter reviews current literature on different methods of measuring innovation and machine learning (ML) techniques used to make predictions. Companies across all sectors, including aerospace and defense companies, work together to bolster innovation to meet the needs of the U.S. military strategy (Ali et al., 2019), improve overall performance, and keep their businesses competitive (El Bassiti & Ajhoun, 2016). With the current accelerating pace of innovation, large firms cannot rely solely on internal research and development (R&D) to meet their innovation goals (Cefis & Triguero, 2016). They augment R&D efforts through the acquisition of innovative companies (Cefis & Triguero, 2016).

Section 2.2 outlines the need for innovation and its importance, its significance to aerospace and defense, and different methods of measuring it. **Section 2.3** describes different ML models, their applicability to the classification of innovation, their advantages and disadvantages, and their metrics. Finally, **Section 2.4** summarizes the literature review and ties the existing research to the goals of this praxis.

2.2 Innovation

Innovation metrics form the foundational basis for this praxis and were used to train ML algorithms for making predictions on acquisitions. This section defines innovation, including the metrics used to quantify it.

2.2.1 Defining Innovation

The end goal of innovation is to provide a firm with a competitive advantage over market players by accelerating new product development (Andersson et al., 2011). One

way to classify innovation is as tangible or intangible (Andersson et al., 2011). Tangible innovation consists of enhancements to core processes, product performance, product systems, and enabling processes. Intangible innovation includes improvements in a business model, networking, services, channels, brands, customer experience, and management (Andersson et al., 2011). Innovation is not only the creation of a new product but also the improvement of tools, processes, and behaviors that lead to that product's creation and adoption within its industry.

Another way to classify innovation depends on product specification (Salomo & Mensel, 2001). Product specification is defined according to three levels:

1. Incremental innovations, where specifications are detailed.
2. Highly innovative products, where specifications are limited and change significantly from initial specification to final product.
3. Medium innovation, where the specifications are detailed throughout the development process, but innovation occurs in the production phase.

The factors that contribute to a company's choice of innovation style involve company size, innovation maturity, and customer intimacy (Salomo & Mensel, 2001).

Innovation can also be classified using three parameters: size by granularity scale (micro, meso, and macro), life cycle by stage (generation, interlinking, improvement, validation, and exploitation), and maturity level (awareness, defined, managed, linked, and sustained; El Bassiti & Ajhoun, 2016). Since this praxis focuses on company-level innovation through acquisitions, macro company-level end-stage innovation was assessed, and tangible, publicly available data were analyzed.

2.2.2 Innovation in Aerospace and Defense

Innovation in the U.S. Defense Force has been a key driver of its superiority (Gholz & Sapolsky, 2021); measuring innovation in this sector presents a unique challenge compared with other sectors. The aerospace and defense industry has distinctive characteristics, including a limited customer base, multiple conflicting criteria and objectives, and hostile and adaptive adversaries (Harrison et al., 2020). These unique characteristics need to be addressed when deciding on a method of measuring innovation, especially measures that account for items related to a more commercial model, have a large customer base, or are driven by factors that do not apply to the defense market.

2.2.3 Measuring Innovation

There is no comprehensive model or general consensus on measuring innovation (El Bassiti & Ajhoun, 2016). Some of the challenges that have been identified include the following:

1. Determining the stage of the innovation process to measure.
2. Identifying the level of the organization (i.e., project, business unit, function, or company) on which to perform the measurement process.
3. Deciding who performs the measurement process (whether internal groups, customers, or third parties).

Historically, market share or new product development were easily quantifiable metrics used to determine the level of innovation. New product development does not always correlate with increased sales or profits (El Bassiti & Ajhoun, 2016; Hong et al., 2017). Therefore, several approaches have been proposed to measure innovation. A more nuanced measure that incorporates perception measurements captured by questionnaires

can comprise a metric that uses subjective scoring (Andersson et al., 2011). The perception measures are based on criteria established by an organization along with quantifiable new product development and company performance measures. By comparing the internal perceptions captured by the questionnaires using the measured metrics, this method provides an overview of the different types of innovation within a company, but it requires subjectivity, and the data must be manually captured (Andersson et al., 2011).

Another method for classifying innovation metrics is using company-specific dimensions (innovation culture, strategy, knowledge and competence, organizational structure, R&D activities and inputs, and financial innovation performance), contextual dimensions (market, network, and environmental), and innovative processes (product definition, product concept, validation phase, production phase, market launch, and innovation process management) (Dziallas & Blind, 2019). Company-specific categorization can also be delineated by knowledge, strategy, organizational structure, and financial dimensions. An additional method relevant to program-focused businesses is portfolio management and project management as categories aimed at the lower levels of a business (Adams et al., 2006).

Input management focuses on the input drivers for innovation, including the staffing and financial elements that generate new products and innovations. R&D intensity is a typical measure used in this area, with R&D spending used as a metric (Adams et al., 2006). Knowledge management correlates with idea generation and the ability to absorb new information. It uses metrics that often align with patent counts or

similar metrics (Sutz, 2012). Commercialization is determined by the release and adoption of new products or processes.

While important in driving innovation, metrics related to innovation strategy, organizational culture and structure, portfolio management, and project management have fewer clear-cut quantifiable measures (Adams et al., 2006). Resource-based metrics are quantifiable, not subjective, and publicly available (Dziallas & Blind, 2019), thus allowing for broad comparisons.

2.2.3.1.1 Resource-Based Metrics

Resource-based metrics involve the assessment of the assets deployed to increase innovation, which can take the form of people, tools, and processes employed or funding (Dziallas & Blind, 2019). The advantage of resource-based metrics is that data are not subjective, allowing for consistency across measures that can change based on the measure's source. Recent research on resource-based metrics has used ratios rather than absolute values more frequently, as this allows the comparison of organizations with different sizes and investment profiles (Dziallas & Blind, 2019). Resource-based metrics are divided into three categories: financial and commercialization metrics, R&D intensity, and patent-based metrics. Financial and commercialization metrics focus on the results of innovation, as innovation impacts business results (Dziallas & Blind, 2019). R&D intensity measures the input required to facilitate the innovation process by measuring a firm's investment in R&D (Dziallas & Blind, 2019). Finally, patent-based metrics use a company's patent information (Dziallas & Blind, 2019).

2.2.3.1.2 Financial and Commercialization Metrics

Metrics that focus on business results and financial performance, such as revenue, new products (Dziallas & Blind, 2019), recent product sales (Caird et al., 2013), and

return on investment (Kim, 2013). These metrics are appropriate for use in ML models as they are non-subjective, quantitative metrics. Due to the complex array of factors aside from innovation that drives business results, financial and commercial factors poorly correlate with innovation, which represents their biggest drawback (Dziallas & Blind, 2019). Moreover, commercialization factors in the defense space are different from those in other industries (Harrison et al., 2020), making both financial and commercialization metrics poor choices for determining the outcomes of defense acquisitions. Although some of these metrics can be normalized for the defense industry, this is outside the scope of this praxis.

2.2.3.1.3 R&D Intensity

R&D intensity measures the input required to facilitate the innovation process by measuring a firm's investment in R&D (Savrul & Incekara, 2015). It has a significant positive correlation with product and process innovation (Song & Oh, 2015). The eight most innovative countries are among the top 10 investors in R&D. R&D intensity also has a positive effect on green innovation (Sánchez-Sellero & Batainehshowed, 2022). To date, this metric has not been used in the defense space.

R&D intensity has a point of negative returns beyond a certain threshold, resulting in an inverted U-shaped relationship between R&D intensity and innovation (**Figure 2-1**). Cash flow acts as a lever in adjusting the point of maximum returns (Xin et al., 2019). Increasing R&D intensity only increases innovation to a maximum, the top of the inverted U, after which innovation decreases as R&D intensity increases. R&D intensity was also shown to correlate negatively with lower short-term profitability but positively with the long-term value of a company (Leung & Sharma, 2021). Several

studies (Paik & Chang, 2015; Xin et al., 2019) showed diminishing returns of R&D intensity after a maximum threshold point is achieved.

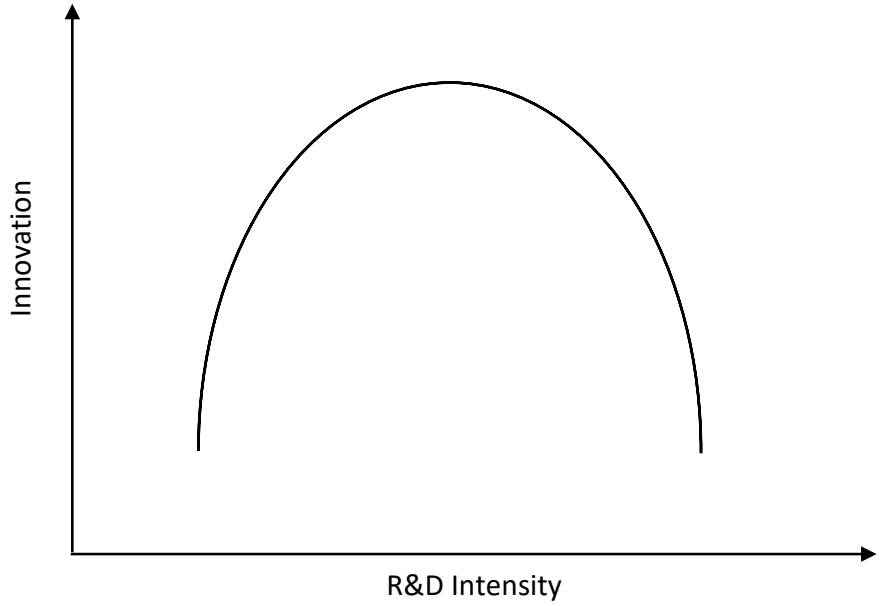

Figure 2-1 Inverted U for R&D Intensity

Patent counts can be used as an R&D output to investigate innovation performance (Cefis & Triguero, 2016). Teng and Yi (2017) found a positive correlation between R&D intensity and innovation performance measured by the volume of patents registered in Chinese commercial companies. It is unclear whether their results are generalizable to U.S. defense organizations due to their unique characteristics as discussed in **Section 2.2.2**. As a measure of innovation, using a patent-based metric directly, in this case, patent registrations, rather than R&D intensity would be a more direct approach, making R&D intensity less ideal.

2.2.3.1.4 Patent-Based Metrics

Assessing patent information is another method used to measure innovation (Abraham & Moitra, 2001; Becheikh et al., 2006; Blind et al., 2006; Cohen et al., 2002;

Kabulova & Stankevičienė, 2020; Lanjouw & Schankerman, 1999; McAleer & Slottje, 2005; Nagaoka et al., 2010; Pakes & Griliches, 1984; Ponta et al., 2021). Patent-based metrics are used for several purposes, including measuring trends and innovation (Abraham & Moitra, 2001). They are attractive as there are large databases of publicly available information on patents and massive computing power available for mining patent data (Nagaoka et al., 2010).

Another advantage of patent-based metrics is the elimination of subjective criteria obtained from surveys or interviews (Ponta et al., 2021). The number of patents can be used to indicate company knowledge, which is directly tied to innovation (Pakes & Griliches, 1984). One drawback is that patent submission importance differs by country, resulting in cultural differences (Cohen et al., 2002). Beyond national differences, companies and industries have different cultures and motivations for patenting ideas, which should be accounted for when measuring across broad markets and industries (Becheikh et al., 2006; Blind et al., 2006).

Lanjouw and Schankerman (1999) studied patent information from 1960 to 1991 and found that patent forward citations and claims were the strongest innovation indicators. Patent renewal has been shown to positively correlate with profitability. Also, patent renewal and patent family positively correlate with innovation (Svensson, 2022).

The patent success ratio (PSR) is a measure that takes absolute values, such as total patents, patent applications, or new product releases, to create a ratio of the number of patents granted to total patent applications (McAleer & Slottje, 2005). Granger tests were used on PSR, patent applications, and inflation-adjusted U.S. gross domestic product (GDP) from 1915 to 2001. PSR had a stronger association with real GDP growth

compared with the growth in successful patent applications as a measure of innovation. PSR could not be directly compared to patent approval applications due to the use of different units.

The PSR presents several advantages as a measure of innovation:

1. The PSR is presented as a ratio, making it possible to compare firms of different sizes and overcoming some of the issues related to patenting approach differences by country, industry, and market (Becheikh et al., 2006; Blind et al., 2006; Cohen et al., 2002; Kabulova & Stankevičienė, 2020).
2. Data using patent information are 100% publicly available, not subjective, and readily available, which may not be true of internal company metrics, such as R&D budgets.
3. The PSR represents all innovation at the company level, not as a subcomponent within the company or specific to a singular process or product.
4. The PSR has a stronger association with real GDP growth than growth in successful patent applications as a measure of innovation.
5. The PSR is superior to financial and commercialization metrics for aerospace defense, as companies in this industry have a unique business model (as described in **Section 2.2.2**), including a limited customer base. For these companies, product sales would not be an accurate commercial signifier due to the limited available market; for example, the market for fighter aircraft is tightly controlled by the U.S. government (O'Conner, 2019).

The core disadvantage of the PSR is that it does not account for larger macroeconomic trends on its own, requiring a normalizing or adjusting factor to compare the PSR across years. To show the correlation between the PSR and GDP, inflation must be accounted for across time.

2.2.4 Mergers and Acquisitions for Innovation

Mergers and acquisitions (M&A) often have adverse effects on innovation performance metrics based on the measurement of patent applications; it is currently unknown whether this holds true for the PSR metric (Ma & Liu, 2017). When measured according to the merger type, mergers of similar companies and conglomerate M&A had an overall negative effect on innovation. The company type, based on both the acquirer and acquiree industries, were used as part of the ML inputs in this study. Although all acquirers are part of the defense industry, the companies have specialties that are reflected in the CrunchBase dataset that may be outside of defense.

Challenges associated with a company acquisition, called post-merger integration (PMI) issues, can be mitigated by pre-acquisition methods, including strategic alliances between companies, the use of corporate venture capital that gives the acquirer more information about the emerging technologies of startups, and broader participation in the startups' ecosystem (Brueller & Capron, 2021). PMI reduction solutions could be implemented by an individual company planning an acquisition or generating a strategy for acquisition but are not relevant to an ML model. It is likely that ML model predictions regarding acquisitions that increase innovation will correlate with companies that implement PMI reduction activities.

2.3 ML Model Analysis

The following subsections give an overview of different ML methods and how they have been applied to innovation and M&A.

2.3.1 ML Techniques

ML can be divided into three paradigms based on the learning method: unsupervised, reinforcement, and supervised learning (Alzubi et al., 2018). Unsupervised learning has no predetermined labels, as the ML algorithm determines the labels based on patterns in the data (Alzubi et al., 2018). Reinforcement learning obtains learning data from feedback on actions rather than from an input data set. Finally, in supervised learning, data are labeled based on a predetermined output or label to enable prediction and classification (Ross et al., 2021; Yang et al., 2014).

Forner et al. (2019) employed an ML approach to analyze innovation performance at the national level using several methods, including clustering, correlation analysis, and artificial neural networks (ANNs). Their findings have shown that ML techniques can be used to benchmark and predict national innovation based on key features. The methods used in their research were all unsupervised, as they are appropriate for understanding and characterizing unlabeled data (Alzubi et al., 2018). Measurements at the national level differ from those for individual companies, as national research is more focused on larger trends encompassing all industries that do not easily translate to individual defense companies.

Guerzoni et al. (2021) used several techniques to analyze startups' innovation using supervised learning, specifically recursive partitioning, classification tree, conditional inference tree, bagging, logit regression, naïve Bayesian classifier, and ANN.

They used these ML models to predict innovation perceptions and firm survival rates for Italian high-tech companies from 2008 to 2013. Although the data were connected to the Italian market and the results may not be applicable outside of the Italian industry, the approach created a precedent for using ML to measure innovation.

Ross et al. (2021) developed an ML model to predict startup outcomes using open-source CrunchBase data and several methods: deep learning, multi-layer perceptron, boosting, random forests, and K-nearest neighbors (KNN). The methods achieved a prediction accuracy rate greater than 80% based on the evaluation of 2000 startups. The model sets a precedent for accurate ML models in a similar area to the praxis, using M&A data to make predictions using CrunchBase datasets.

2.3.1.1 Naïve Bayes

The naïve Bayes method is a supervised learning algorithm based on applying Bayes' theorem with the assumption that every pair of features is independent (Mahdavinejad et al., 2018). The advantage of this algorithm is that it is fast and scales well; this comes at the cost of lower accuracy (Korotcov et al., 2017). Naïve Bayes was shown to be only slightly better than random chance when forecasting patent applications, although no research has been done using the PSR metric (Guerzoni et al., 2021).

2.3.1.2 Decision Tree

The decision tree approach is a supervised model that can be used for both classification and regression (Pandey et al., 2020). It generates a model with decision points based on the entropy of the input data. The decision point will end in a final value (Choudhary & Gianey, 2017). Advantages include speed and the ability to understand

how the model came to its decision (Brownlee, 2020). Decision trees typically have lower accuracy than other ensemble models, such as random forest (Bai & Zhao, 2021), but they can visualize the decision-making process (Ye, 2011).

2.3.1.3 Support Vector Machine

Support vector machine (SVM) is a supervised learning model that can be used for classification problems (Choudhary & Gianey, 2017). It uses a hyperplane to separate the data into classes by label (Bai & Zhao, 2021). The kernel function, which provides the best largest margin between the hyperplane and data points, provides the best classification performance (Korotcov et al., 2017). An SVM using the radial basis function as its kernel performed worse than KNN in classifying molecular properties (Rácz et al., 2019); SVM was used to successfully classify text on startups into three classes (Saura et al., 2019).

2.3.1.4 K-Nearest Neighbors

KNN is a supervised, non-parametric method that can be used for classification and regression (Alzubi et al., 2018). It uses distance measures from known data points to extrapolate the classification of an unknown one, with the K representing the number of data points used to estimate the unknown one (Mahdavinejad et al., 2018). Multiple functions can be used to determine the distance, with Euclidean, Manhattan, and Minkowski distances being the most common ones, but for categorical data, Hamming distance must be used (Choudhary & Gianey, 2017). The biggest disadvantage of the KNN algorithm is its lack of scalability because it requires the entire training set to be in memory (Mahdavinejad et al., 2018). KNN was shown to perform more poorly on

classification tasks compared with SVM and a boosting method when classifying startup data from CrunchBase (Ross et al., 2021).

2.3.1.5 Artificial Neural Networks

ANNs are based on biological functions and operate similarly to neurons, consisting of input, output, and hidden layers between the inputs and outputs (Abiodun et al., 2018). The biggest advantage of ANNs is their ability to determine relationships from datasets, while the biggest disadvantage is that there is no way to understand how the ANN made those decisions. ANNs can be adjusted by modifying the number of hidden layers and the number of components within a layer. Adding additional hidden layers and nodes leads to higher accuracy but can result in overfitting (Ross et al., 2021). ANNs were employed using patent data to predict company outcomes and successfully applied to research related to predicting startup exits (Ross et al., 2021) and startup investments **(**Bai & Zhao**,** 2021).

2.3.1.6 Ensemble Models

Ensemble models combine several ML techniques into one, either sequentially or in parallel, to reduce errors or variability or improve predictions (Alzubi et al., 2018). Ensemble models are better at predicting skewed data, in which the label used for training is not evenly distributed within the dataset (Yang et al., 2014). Yang et al. (2014) used an ensemble model to study M&A activity based on the profiles of bidders and sellers. The researchers combined several different methods in their model, including bagging and AdaBoost, with one of the inputs being patent activity. Their analysis reached a recall rate of slightly less than 75% in its most accurate model and achieved > 90% accuracy when predicting technology M&A (Yang et al., 2014), exceeding the

performance of a single learner. These findings support that ensemble models could successfully accept patent data to make predictions. In another study (Krishna et al., 2016), an ensemble model performed the best against individuals when predicting startup outcomes.

2.3.1.6.1 Random Forest

Random forests are parallel ensemble models that use multiple decision trees, in which each tree is trained on a subset of the training data (Mahdavinejad et al., 2018). The random forest technique combines the input decision trees by creating a two-level structure, allowing it to make predictions (Alzubi et al., 2018). The advantage over a single decision tree is its additional analytical abilities and reduced variance (Bai & Zhao, 2021). Random forests have achieved receiver operating characteristic (ROC)–area under the curve (AUC) scores over 0.9 based on an analysis of 11,000 startups (Krishna et al., 2016). An AUC of 0.9 is considered an excellent fit for a model (Fawcett, 2006).

2.3.1.6.2 Boosting

Boosting is a sequential, iterative technique that adjusts the weighting of observations based on the last classification, adapting a weak learner model sequence that performs better than pure random prediction (Alzubi et al., 2018). Boosting has been shown to achieve better results than naïve Bayes and has comparable results to SVM and random forests (Korotcov et al., 2017).

2.3.1.6.3 Ensemble Averaging

Ensemble averaging is a parallel ensemble technique that combines heterogeneous models by averaging the probability of each model's output (Sarkar & Natarajan, 2019). The ensemble averaging model overcomes the issue of lower accuracy in ensemble models due to poor classifier combination selection (Alzubi et al., 2018).

The advantage of this model is that it uses multiple methods that include different approaches to obtain their results, allowing the methods to complement each other by avoiding weaknesses and combining strengths. This method has been used in M&A analysis to obtain improved metrics (accuracy, AUC, precision, recall, and F1 score) over a single learner (Yang et al., 2014).

2.4 Summary and Conclusion

To remain competitive, technology companies must continuously foster innovation (El Bassiti & Ajhoun, 2016). A subset of technology companies, aerospace and defense, faces the same requirement to remain competitive in the market as a direct result of the U.S. government's increasing reliance on technology as a national doctrine (Ali et al., 2019).

Internal R&D spending alone is not enough to address innovation needs, so defense companies often pursue open and external innovation methods, such as M&A, to support their R&D (Cefis & Triguero, 2016). One challenge with making acquisitions to foster innovation is that integrating external innovation can disturb internal efforts (Trichterborn et al., 2016). To avoid this adverse impact, clear metrics are needed to measure innovation levels and predict the impact of acquisitions.

There are several metrics for determining innovation, each with different levels of subjectivity and challenges to data collection. The PSR is a quantitative metric that is generated using publicly available information and is tied to the goal of innovation, providing a firm with a competitive advantage over its peers (McAleer & Slottje, 2005). With a metric that is easily generated from a large dataset of publicly available information, ML methods can be used to understand the factors related to acquisitions

from the data (Alzubi et al., 2018). Different ML models have been used to assess companies based on publicly available factors. ML models have different strengths and weaknesses with ensemble models being common because of their ability to make strong learners by combining several weaker ones (Ross et al., 2021; Yang et al., 2014). Ensemble models of boosting, random forest, and ensemble averaging require more processing, but also provide more accurate results, because of their multiple methods of analysis. Ensemble ML models have been successful in making predictions with an accuracy of more than 70% on publicly available company data (Ross et al., 2021). Of the non-ensemble models, Naïve Bayes is expected to offer the fastest analysis times but provide the least accurate results. The SVM, KNN, and decision tree models all are expected to perform between the naïve Bayes model and the ensemble models.

Research has successfully measured innovation and the success of acquisitions, but there has not been any work that combined the two using ML methods and publicly available datasets. Additionally, none of the previous work focused specifically on defense acquisition and innovation, regardless of the use of ML techniques.

Methodology

3.1 Introduction

Chapter 3 documents the approach taken in answering the research questions and testing the hypotheses presented in Chapter 1. It also summarizes the data sources, their methods of collection, and the rationale for their use. The analyses used to test the hypotheses are explained to ensure the research's replicability. Finally, the derivation of the machine learning (ML) evaluation metrics and the rationale for their use are discussed in detail.

This chapter is organized as follows: **Section 3.2** discusses the methods and sources used during data collection. **Section 3.3** describes the preprocessing approaches used in the ML analysis including the methods for calculating the patent success ratio (PSR) and data cleansing. The method for identifying the statistical significance of acquisitions to PSR is presented in **Section 3.4**. **Section 3.5** explains the details of the eight ML methods: naïve Bayes, decision tree, support vector machine (SVM), k-nearest neighbors (KNN), artificial neural network (ANN), random forest, boosting, and an ensemble model using averaging. Finally, **Section 3.6** discusses the data validation techniques, and **Section 3.7** details the metrics used to evaluate the ML algorithms.

3.2 Data Collection

Data collection followed a three-step process:

1. Identifying defense companies and information about those companies that can be used in an ML model.
2. Collecting data on the acquisition events of the identified defense companies, including metrics of the companies acquired and the events themselves.

3. Gathering patent information for the acquiring defense companies before and after the acquisition events.

All data were publicly available online so that the developed tools could be used by an outside firm analyzing the potential purchase of a startup.

3.2.1 Defense Company Selection

The Stockholm International Peace Research Institute (SIPRI) is an international think tank that studies armaments and arms control. Each year, it tracks and publishes a list of the top 100 global defense companies ranked by sales (McGann, 2021). Companies were selected from this yearly list according to the following criteria:

1. The companies had a presence in the US, as innovation priorities vary between countries, with a focus on innovation as part of its strategy.
2. The companies had to be on the list for at least 6 years between 2002 and 2020 to ensure that only companies with consistent performance were measured.

A total of 34 companies that met these criteria were included in this praxis. Appendix A shows the list of companies.

3.2.2 Startup Acquisition

Acquisition event data of the selected companies were collected from CrunchBase, an online platform hosting a crowdsourced database of over one million startups and their related information (Ross et al., 2021). CrunchBase is frequently used in research related to startups, including in selection, exit analysis, and venture funding (Bonini & Capizzi, 2019; Keogh & Johnson, 2021; Kim et al., 2022; Krishna et al., 2016; Ross et al., 2021; Zhong et al., 2018). The acquisition dataset used in this praxis was

retrieved in May 2022 and included details of 417 acquisition events by the 34 companies sourced from the SIPRI list. Appendix B shows the fields from the acquisition dataset.

3.2.3 Patent Information

The US Patent and Trademark Office (USPTO) hosts a publicly available database of all patent applications and their statuses which served as the source for all patent data in this praxis. Lens Labs is an open collaboration that provides a front-end interface for researchers to search the USPTO patent database and provides analysis through its website (Lens Labs, n.d.). A total of 149,501 patent applications and grants were collected for the 34 defense companies in the period 1993–2021.

3.3 Preprocessing of Input Data Sets

The collected datasets were processed in several steps to generate the following three datasets used during the final analysis:

1. Dataset 1: Acquisition Significance: Used to determine whether there is significance between the number of acquisitions and innovation.
2. Dataset 2: 3-Year PSR: Used to develop ML models in predicting innovation changes over a 3-year period from defense acquisitions.
3. Dataset 3: 5-Year PSR: Used to develop ML models in predicting innovation changes over a 5-year period from defense acquisitions.

Figure 3-1 shows the workflow for processing the collected data to obtain the final datasets. Of the innovation metrics described in **Section 2.2.3.1**, PSR was selected as the metric for innovation in this praxis. Calculating the PSR is the first processing step in the flow, followed by cleaning the CrunchBase acquisition data and finally combining the datasets.

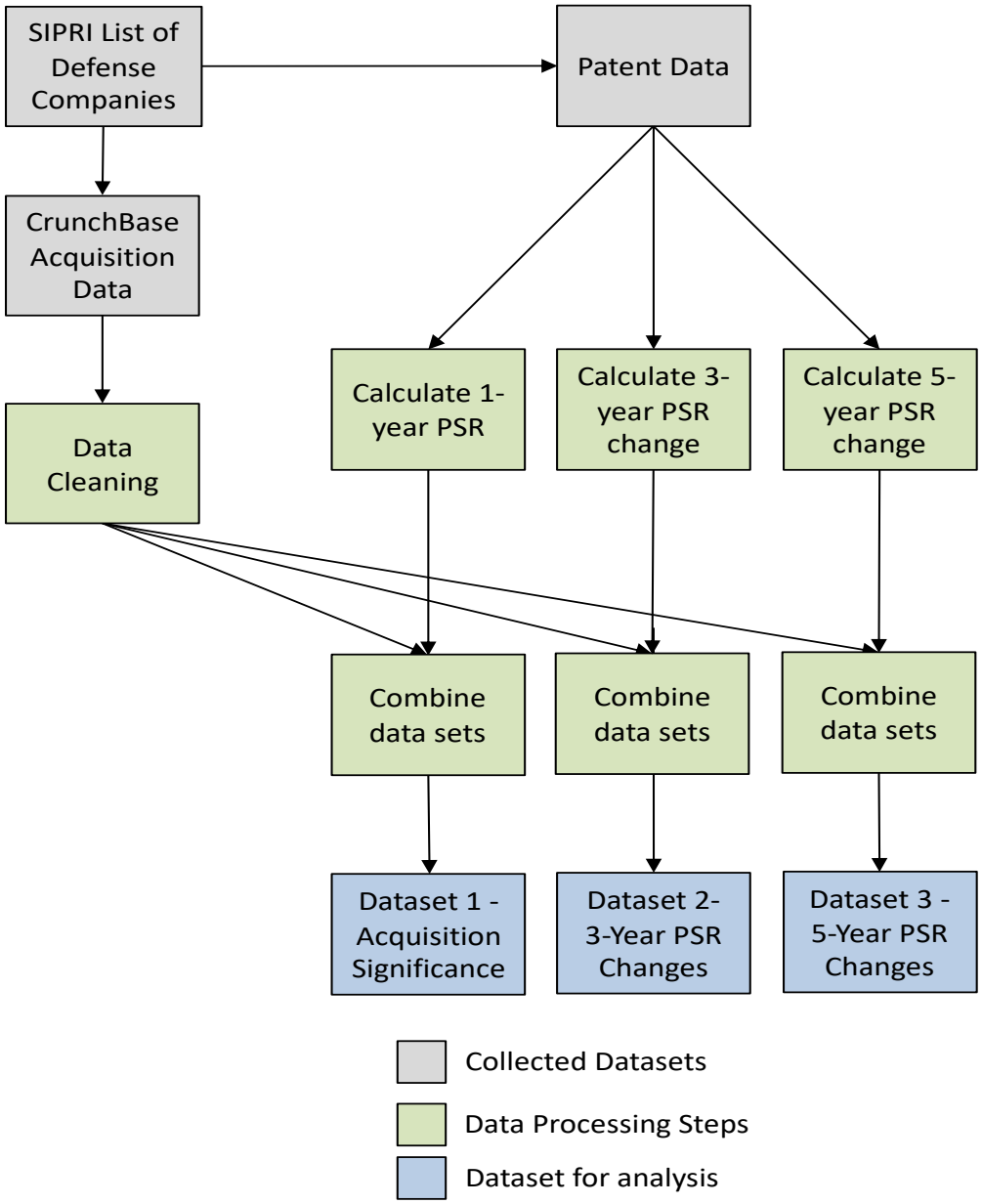

Figure 3-1 Dataset Analyses Workflow

3.3.1 Calculating the Patent Success Ratio

PSR is calculated by dividing the number of patents granted by the total number of patent applications (McAleer & Slottje, 2005) as in **Equation 3-1**. In this equation, the total number of patent applications is the sum of the number of patent applications that were granted and patent applications that were not granted.

$$PSR = G/ (G+A)$$

Equation 3-1 Formula for PSR

where,

PSR is the Patent Success Ratio,

G is the number of patents granted, and

A is the number of patent applications without being granted.

PSR cannot be compared across years without a normalizing factor to adjust for changes over time (McAleer & Slottje, 2005). Therefore, a normalizing factor was applied to adjust the PSR for macroeconomic trends, allowing comparisons of individual companies. This normalizing factor calculates the PSR for all patents each year. The calculated PSR for each company was divided by the yearly PSR to obtain the normalized PSR, according to **Equation 3-2**.

$$NPSR = PSR/PSR*$$

Equation 3-2 Formula for normalized PSR

where,

NPSR is the normalized PSR,

PSR is the Patent Success Ratio PSR, and

*PSR** is the PSR for all patents

The 1-year PSR was calculated yearly for each defense company. Calculation of the **3-year PSR change** and **5-year PSR change** was performed as follows:

1. PSR was calculated before and after acquisition using **Equations 3-3** and **3-4**.

2. The pre- and post-PSR data were normalized by dividing the pre- and post-acquisition PSR values by a normalized PSR for all patents that was based on the average PSR for all patents (**Equation 3-2)**. Normalization was needed to compensate for year-to-year PSR changes due to global impacts such as recessions.
3. Pre- and post- values were compared and a value of *increase* or *decrease* was assigned to the acquisition. For PSR post-acquisition values greater than pre-acquisition values, a value of *increase* was assigned to the acquisition, while lower post-acquisition values were assigned a value of *decrease*. There were no instances where the post-acquisition value was the same as the pre-acquisition one.

$$\text{PSR Pre Acquisition} = \frac{\sum_{n=0}^{d-1} (G)_{\text{Y-n}}}{\sum_{n=0}^{d-1} (G + A)_{\text{Y-n}}}$$

Equation 3-3 PSR Pre-Acquisition Formula

where,

G is the number of patents granted,

A is the number of patent applications without being granted,

Y is the acquisition year, and

d is the time period for PSR calculation: d = 3 for a 3-year PSR change and a d = 5 for 5-year change

$$\text{PSR Post Acquisition} = \frac{\sum_{n=1}^{d} (G)_{Y+n}}{\sum_{n=1}^{d} (G + A)_{Y+n}}$$

Equation 3-4 PSR Post-Acquisition Formula

where,

G is the number of patents granted,

A is the number of patents applications without being granted,

Y is the acquisition year, and

d is the time period for PSR calculation: d = 3 for a 3-year PSR change and d = 5 for a 5-year change.

3.3.2 CrunchBase Acquisition Data Cleaning

Data from the CrunchBase dataset was refined as follows:

1. Data fields with multiple values in a field were separated into their own columns.
2. Fields with values that were 95% the same were pruned.
3. Companies that were acquired more than once were pruned.
4. Categories were added to indicate whether startups and acquirers were headquartered in the same region.
5. Categories were added to calculate the number of acquisitions in previous years.
6. Categorical data were encoded using dummy encoding ahead of the ML algorithm application.

3.4 Method for Determining the Statistical Significance of Acquisitions

Multiple regression analysis was used to determine whether there was a statistically significant increase in the acquiring firm's normalized PSR and number of acquisitions. The independent variables used in the regression were the year of announcement, number of acquisitions, and acquiring company. Acquiring companies were encoded using dummy encoding to allow for the analysis. The dependent variable was the normalized PSR value by year. A standard *p*-value of 0.05 was used to determine whether the relationship was statistically significant (Fisher, 1992).

3.5 Machine Learning Methods

Eight ML methods were utilized in this praxis: naïve Bayes, decision tree, SVM, KNN, ANN, random forest, boosting, and an ensemble model using averaging. These ML algorithms aim to provide defense companies with a predictive model for selecting startups that will increase company innovation. The ML models were developed in the Dataiku Design Science Studio (DSS) 11.0.1 Design Science and Machine Learning platform with a Python version 3.7 back end.

For each acquisition, the models output a category with one of two labels - increase or decrease - relative to PSR.

3.5.1 Naïve Bayes Model

The naïve Bayes model was implemented with the Gaussian naïve Bayes algorithm in Python using the GaussianNB function within the **sklearn.naive_bayes library** (Pedregosa et al., 2011).

3.5.2 Decision Tree Model

DSS's built-in decision tree classifier algorithm was used to implement the decision tree model. Hyperparameter optimization was used to determine the maximum depth of the tree and the minimum number of samples per leaf.

Trial and error were used to determine the function of measuring the quality of a split and the split strategy. The 3-year prediction was split based on entropy, while the 5-year prediction used Gini. The split strategy was the same for both methods, using the best split rather than a random split. **Tables 3-1** and **3-2** show the hyperparameters used for the 3-year model and 5-year model, respectively.

Table 3-1 Hyperparameters for 3-Year Prediction using Decision Tree

Algorithm	Decision tree classifier
Max tree depth	5
Split criterion	entropy
Min samples per leaf	1
Splitter	best

Table 3-2 Hyperparameters for 5-Year Prediction using Decision Tree

Algorithm	Decision tree classifier
Max tree depth	6
Split criterion	Gini
Min samples per leaf	20

3.5.3 Support Vector Machine Model

DSS's built-in SVM classifier algorithm was used to implement the SVM model. Hyperparameter optimization was used to determine the penalty parameter (C) and the

kernel coefficient (gamma). The SVM model creates a hyperplane that separates the data into different classes by label (Choudhary & Gianey, 2017). The kernel function used to define the shape of the hyperplane was chosen because it showed the best results in accuracy and receiver operating characteristic (ROC)–area under curve (AUC) through experimentation with a polynomial kernel. **Tables 3-3** and **3-4** show the hyperparameters used for the 3-year model and 5-year model, respectively.

Table 3-3 Hyperparameters for 3-Year Prediction using SVM

Algorithm	SVM classifier
Kernel	poly
Kernel coef (gamma)	1
C	1
Independent kernel term	0

Table 3-4 Hyperparameters for 5-Year Prediction using SVM

Algorithm	SVM classifier
Kernel	rbf
Kernel coef (gamma)	scale
C	10

3.5.4 K-Nearest Neighbor Model

DSS's built-in KNN classifier algorithm was used to implement the KNN model. Hyperparameter optimization was implemented on the number of neighbors to examine each sample (K). The KNN uses distance measures from known data points to extrapolate the classification of an unknown one (Mahdavinejad et al., 2018). The *p*-value was set to

2, giving the Euclidean distance (Dataiku, 2022). **Tables 3-5** and **3-6** show the hyperparameters used for the 3-year model and 5-year model, respectively.

Table 3-5 Hyperparameters for 3-Year Prediction using KNN

Algorithm	KNN
K	5
Distance weighting	No
p	2

Table 3-6 Hyperparameters for 5-Year Prediction using KNN

Algorithm	KNN
K	5
Distance weighting	No
p	2

3.5.5 Artificial Neural Network Model

DSS's built-in ANN classifier algorithm was used to implement the ANN model. Many different configurations were tested by tuning the number and size of hidden layers, the L2 regularization parameter, the activation function, and the solver. The best results were achieved with two hidden layers of 10 and 100 neurons. The other parameters are documented in **Table 3-7**. The rectified linear activation function (ReLU) was used for the activation function. ReLU cancels negative values obtained in earlier layers (Ciaburro & Iannace, 2021). The limited-memory Broyden–Fletcher–Goldfarb–Shanno algorithm (LBFGS) was used as the algorithm's solver. LBFGS is a batch algorithm appropriate for

smaller datasets, but it does not scale well to larger ones (Liu & Nocedal, 1989). **Table 3-7** shows the hyperparameters used for both the 3-year model and 5-year models.

Table 3-7 Hyperparameters for Prediction using ANN

Algorithm	Artificial Neural Network
Activation	ReLU
Alpha	0.001
Solver	LBFGS

3.5.6 Boosting Model

The boosting model selected was adaptive boosting (AdaBoost), which is the most used boosting algorithm (Alzubi et al., 2018). AdaBoost was implemented in Python using the AdaBoostClassifier function within the **sklearn.ensemble library** (Pedregosa et al., 2011). Experiments were carried out to determine the ideal number of classifiers, with the value of 20 achieving consistent results.

3.5.7 Random Forest Model

DSS's built-in random forest classifier algorithm was used to implement the random forest model. Hyperparameter optimization using 5-fold cross-validation was used to select the values for the number of trees in the forest, maximum tree depth, and minimum samples per leaf. At each split, 30% of the features were selected. **Tables 3-8** and **3-9** show the hyperparameters used for the 3-year model and 5-year model, respectively.

Table 3-8 Hyperparameters for 3-Year Prediction using Random Forest

Algorithm	Random forest classification
Number of trees	140
Max trees depth	13
Min samples per leaf	1
Min samples to split	3
Split quality criterion	Gini

Table 3-9 Hyperparameters for 5-Year Prediction using Random Forest

Algorithm	Random forest classification
Number of trees	200
Max trees depth	20
Min samples per leaf	1
Min samples to split	3
Split quality criterion	Gini

3.5.8 An Ensemble Using Averaging Model

This ensemble model used DSS's built-in Python ensemble classifier with averaging. Different combinations of learners were tested. The best results for the 3-year model are shown in **Figure 3-2**. The most accurate 5-year model was the same as the 3-year model, with the exception that it did not use the KNN learner.

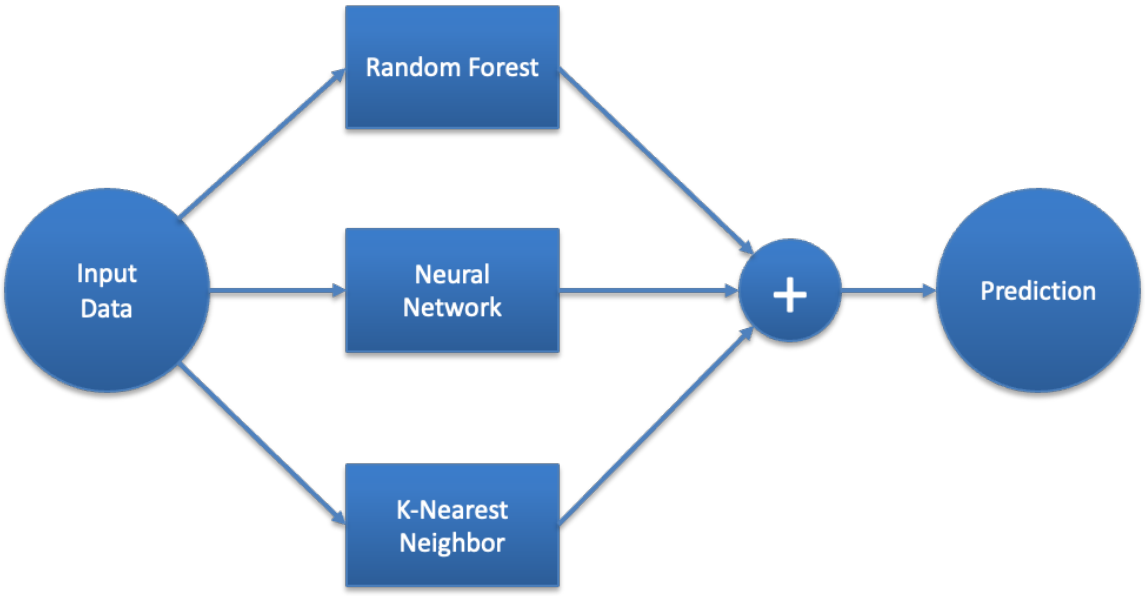

Figure 3-2 Ensemble Model Using Averaging to Combine Learners

3.6 Data Validation

For all models except the averaging ensemble model, validation was performed by splitting the data set, using 80% to train the models and withholding 20% to test the models once they were completed. The 80% training data used 5-fold cross-validation to tune the hyperparameters and validate the model. The model was then tested on 20% of the data that was held back from the training. The performance metrics refer only to the results of that 20% of the data. **Figure 3-3** shows the flowchart of the end-to-end data validation and verification.

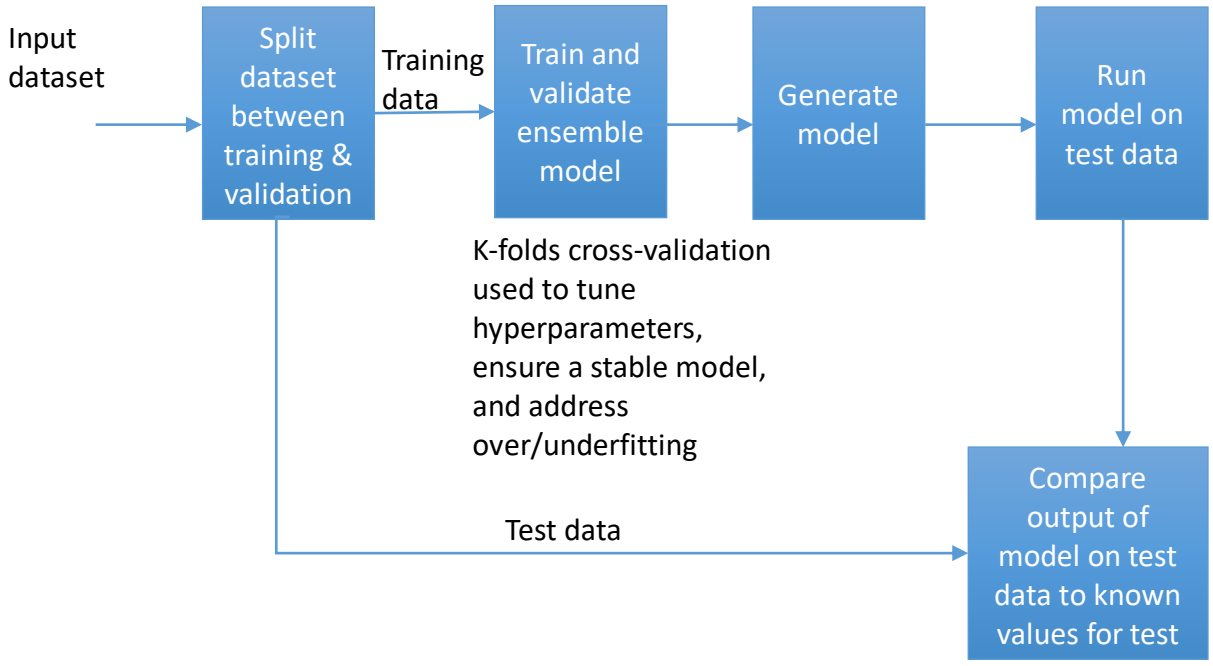

Figure 3-3 Validation and Verification methodology for ML algorithms

For the averaging ensemble model, the dataset was split into 60% training data, 20% validation data, and 20% test data. The 60% training data used 5-fold cross-validation to tune the model, followed by the 20% validation to validate the model. The final 20% of the test data were used to test the model. The performance metrics refer only to the results of the test data.

3.7 Model Performance Evaluation Metrics

Section 2.3.3 describes the list of metrics used to measure the classification models. For this research, confusion matrices, ROC graphs, accuracy, precision, recall, and F1 metrics were used to evaluate the performance of the different ML models. Accuracy alone can be misleading as a measure of ML performance because the trained feature, PSR, is unbalanced, with more acquisitions resulting in decreasing PSR rather

than increasing PSR. With skewed data, accuracy tends to be biased toward the majority category (Yang et al., 2014).

Model performance evaluation metrics measure classification by comparing the values predicted by the ML algorithm with the actual values from test data and dividing them into positive and negative prediction pairs in a confusion matrix (Choudhary & Gianey, 2017). **Table 3-10** defines the confusion matrix used in the classification of correctness in selections. The values true positive (TP), false positive (FP), true negative (TN), and false negative (FN) were used for the evaluation metrics (Choudhary & Gianey, 2017). TP and TN are the number of times the model correctly predicts the positive class and negative class, respectively. FP represents the number of incorrect classifications in the positive class. FN is the equivalent of the FP but for the negative class.

Table 3-10 Confusion Matrix

	Predicted + (PP)	**Predicted – (PN)**
Actual Positive (P)	True positive (TP)	False negative (FN)
Actual Negative (N)	False Positive (FP)	True negative (TN)

Performance metrics were derived from the four measured classification values: TP, FP, FN, and TN.

$$\text{Accuracy} = (TN + TP) / (TN + FP + FN + TP)$$

Equation 3-5 Accuracy Calculation

where,

TN is the number of true negatives,

TP is the number of true positives,

FP is the number of false positives, and

FN is the number of false negatives.

$$TPR = TP / (TP + FN)$$

Equation 3-6 True Positive Rate (TPR) (Sensitivity, Recall, Hit Rate) Calculation

where,

TPR is the True Positive Rate,

TP is the number of true positives, and

FN is the number of false negatives.

$$FPR = FP / (FP + TN)$$

Equation 3-7 False Positive Rate (FPR) Calculation

where,

FPR is the false positive rate,

FP is the number of false positives, and

TN is the number of true negatives.

$$PPV = TP / (TP + FP)$$

Equation 3-8 Positive Predictive Value (PPV) (Precision) Calculation

where,

PPV is the positive predictive value,

TP is the number of true positives, and

FP is the number of false positives.

$$NPV = TN/ (TN + FN)$$

Equation 3-9 Negative Predictive Value (NPV) Calculation

where,

NPV is the negative predictive value,

TN is the number of true negatives, and

FN is the number of false negatives.

$$F1 = TP / (TP + ½ (FP + FN))$$

Equation 3-10 F1 Score Calculation

where,

F1 is the F1 score,

TP is the number of true positives,

FP is the number of false positives, and

FN is the number of false negatives.

The other metric used for classification, which also accounts for skewed data, is the ROC diagram, which visualizes performance metrics by plotting the TPR versus the FPR (Fawcett, 2006). The AUC of the ROC diagram distills the ROC curve into one metric, with a value of 1.0 being a completely accurate classifier (Fawcett, 2006).

Results

4.1 Introduction

This chapter presents the results obtained from the data analysis of the datasets outlined in **Section 3.2**. These datasets include the significance testing test and the eight machine learning (ML) predictive models: naïve Bayes, decision tree, support vector machine (SVM), K-nearest neighbor (KNN), neural network, boosting using AdaBoost, random forest, and an averaging ensemble model.

Section 4.2 reviews the three datasets used in the analysis and the key variables. **Section 4.3** presents the results corresponding to Hypothesis 1. **Sections 4.4–4.11** present the results from each ML method and Hypotheses 2 through 9. The results include a confusion matrix of test result outputs, a list of performance metrics (receiver operating characteristic [ROC]–area under curve [AUC] score, accuracy, precision, recall, and F1 score), and the ROC graph for each model. Finally, **Section 4.12** presents the validation information for each model, showing the results of the analysis described in **Section 3.6**.

4.2 Exploratory Data Analysis

Three datasets were used for this analysis. The first was a list of acquisitions by company and year with a normalized patent success ratio (PSR) for each year. This dataset was used to determine the relationship between the number of acquisitions and the PSR score. The acquiring companies' names were converted to numbers using dummy encoding to perform the regression analysis used for H1. **Figure 4-1** shows the distribution of the three variables used in the H1 analysis.

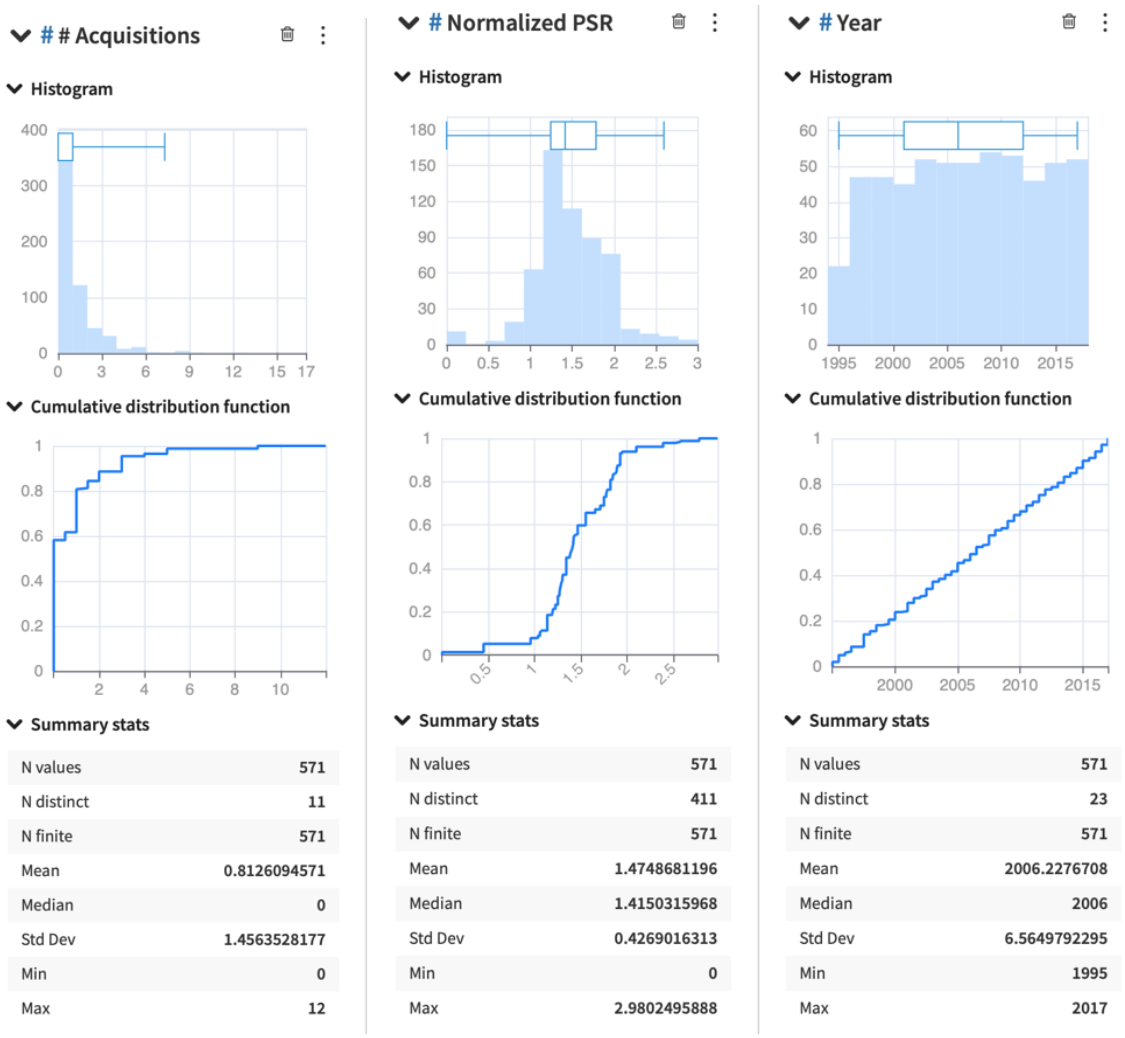

Figure 4-1 Distribution of dataset used for H1 analysis.

The second dataset consisted of defense acquisitions from 1995 to 2017. The models were trained on the **PSR Change** feature derived in **Section 3.1–3.3**. This feature is imbalanced, meaning that the distribution of the feature is not the same for the two possible values and more acquisitions lead to a decrease rather than an increase in PSR score. **Figure 4-2** shows the distribution for both outcomes of the **PSR Change** feature.

The third dataset used a PSR value based on a 5-year period rather than 3 years. This dataset consisted of defense acquisitions from 1999 to 2014. It was also unbalanced for the training feature, as shown in **Figure 4-2**.

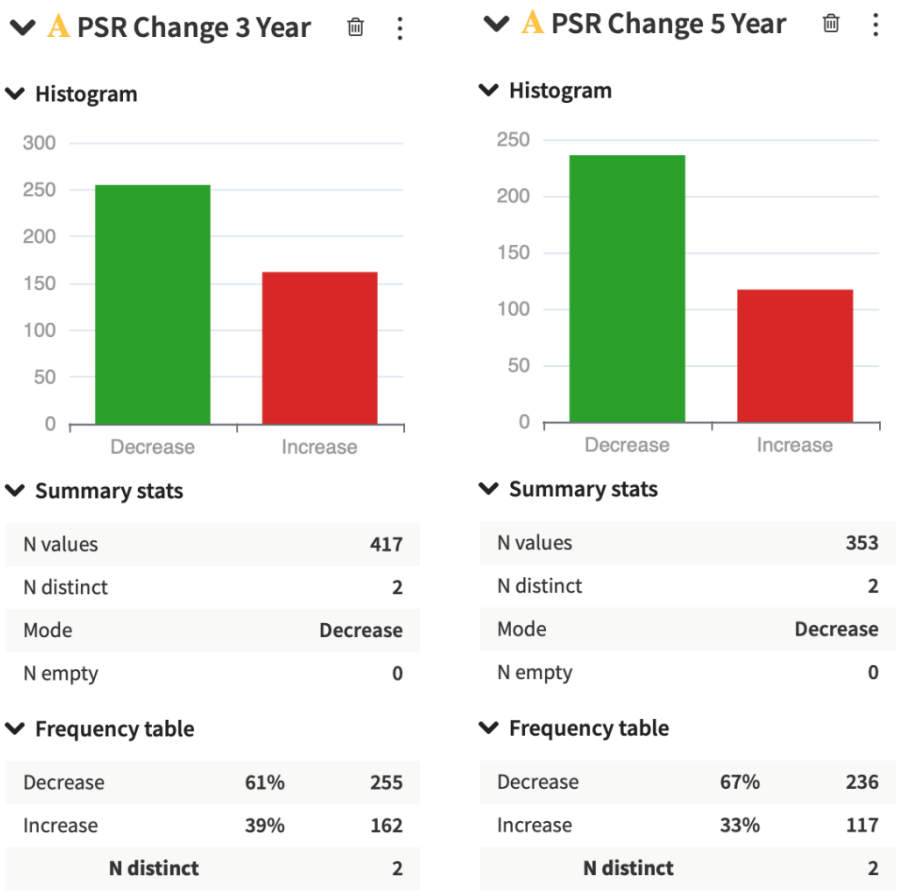

Figure 4-2 Distribution of the target variable for the 3-year (left) and 5-year (right) used to train the ML models

4.3 Hypothesis 1 Results

H1: *Startup acquisitions are associated with a statistically significant increase in the PSR of the acquiring company post acquisition.*

Multiple regression with three variables (year, PSR, and number of acquisitions) was performed in Microsoft Excel to determine the significance of the number of

acquisitions on PSR changes. The results showed that the number of acquisitions was not significantly associated with the PSR of the acquiring company post acquisition (*p*-value = 0.462; **Table 4-1**). **Figure 4-3** displays the histogram of the residuals used in the regression, showing normalcy. A discussion of these results is presented in **Section 5.1.1**.

Table 4-4-1 Results of the multi-regression analysis to determine the significance of the number of acquisitions on PSR changes

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.325729	45.25%	41.78%	32.92%

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value
Regression	34	47.01	1.383	13.03	0.000
# Acquisitions	1	0.058	0.058	0.54	0.462
Year	1	18.089	18.089	170.49	0.000
Error	536	56.869	0.106		
Total	570	103.880			

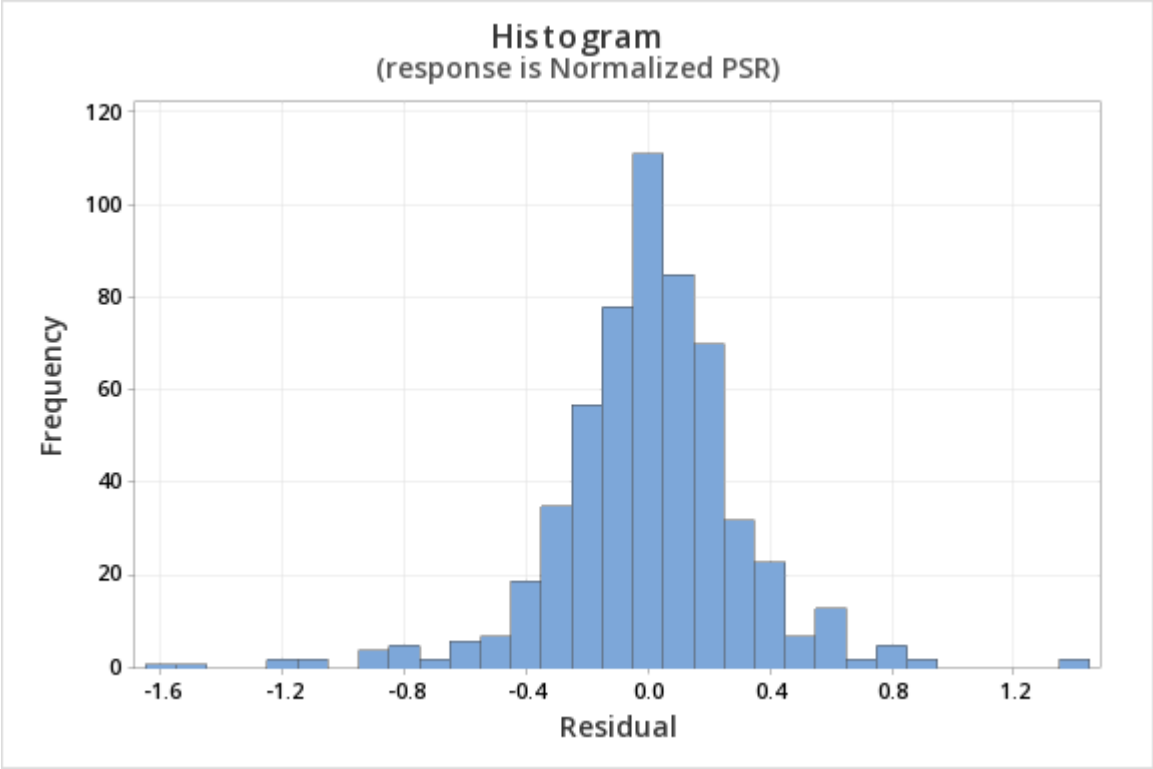

Figure 4-3 The plot of residuals for number of acquisitions related to PSR

4.4 Hypothesis 2 Results

H2: *A naïve Bayes network can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

This section covers the results of the naïve Bayes ML model. **Table 4-2** shows the confusion matrix for the 3-year model. **Table 4-3** presents the performance metrics for the 3-year model against the test dataset. **Figure 4-4** exhibits the ROC chart for the 3-year model. **Tables 4-4** and **4-5** demonstrate the confusion matrix and performance metrics for the 5-year model, respectively. **Figure 4-5** illustrates the ROC chart for the 5-year model. A discussion of these results is presented in **Section 5.1.2**.

Table 4-2 Confusion matrix for Naive Bayes 3-year PSR prediction

	Predicted Increase	Predicted Decrease	Total
Actually Increase	24	2	26
Actually Decrease	51	6	57
Total	75	8	83

Table 4-3 Naïve Bayes performance metrics for 3-year PSR prediction

ROC–AUC Score	0.514
Accuracy	0.361
Precision	0.320
Recall	0.923
F1 Score	0.475

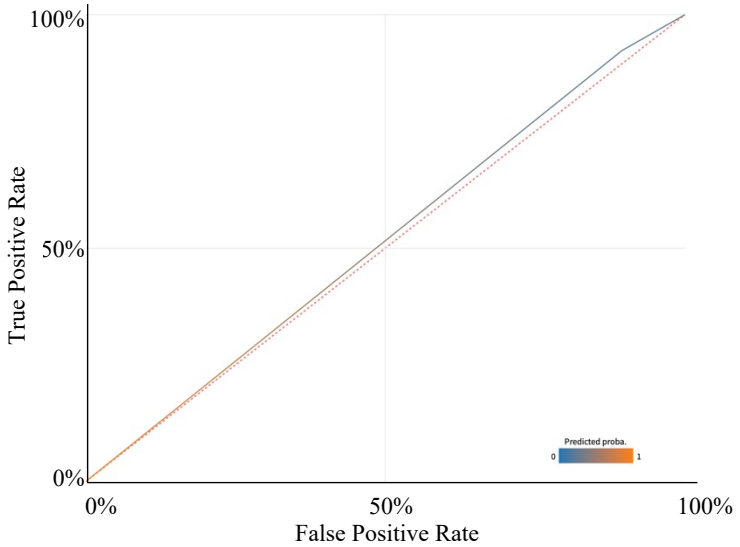

Figure 4-4 ROC graph of naïve Bayes for 3-year PSR prediction

Table 4-4 Confusion matrix for Naive Bayes 5-year PSR prediction

	Predicted Increase	Predicted Decrease	Total
Actually Increase	23	3	26
Actually Decrease	21	23	44
Total	44	26	70

Table 4-5 Naive Bayes performance metrics for 5-year PSR prediction

ROC–AUC Score	0.724
Accuracy	0.657
Precision	0.523
Recall	0.885
F1 Score	0.657

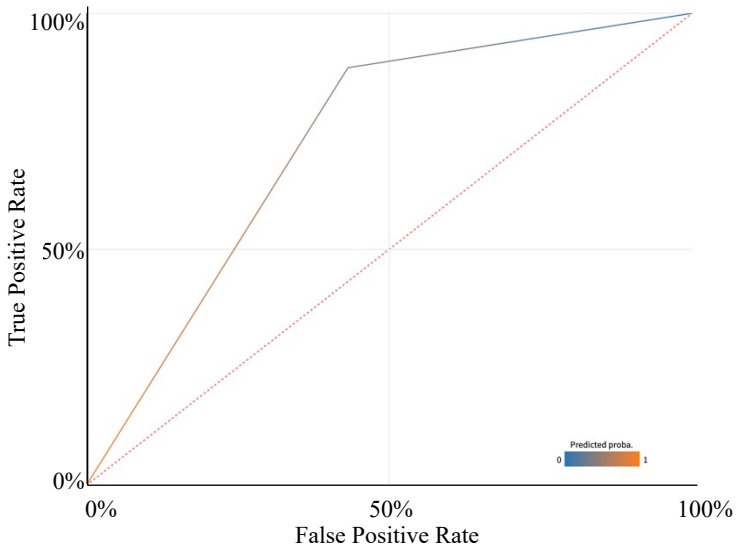

Figure 4-5 ROC graph of naïve Bayes for 5-year PSR prediction

4.5 Hypothesis 3 Results

H3: *A decision tree model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

This section contains the results of the decision tree machine learning model. **Table 4-6** shows the confusion matrix for the model. **Table 4-7** presents the performance metrics for the 3-year model against the test dataset. **Figure 4-6** shows the ROC chart for the 3-year model. **Tables 4-8** and **4-9** demonstrate the confusion matrix and performance metrics for the 5-year model, respectively. **Figure 4-7** illustrates the ROC chart for the 5-year model. A discussion of these results is presented in **Section 5.1.3**.

Table 4-6 Confusion matrix for decision tree 3-year PSR prediction

	Predicted Increase	**Predicted Decrease**	**Total**
Actually Increase	22	4	26
Actually Decrease	29	28	57
Total	51	32	83

Table 4-7 Decision tree performance metrics for 3-year PSR prediction

ROC–AUC Score	0.755
Accuracy	0.602
Precision	0.431
Recall	0.846
F1 Score	0.571

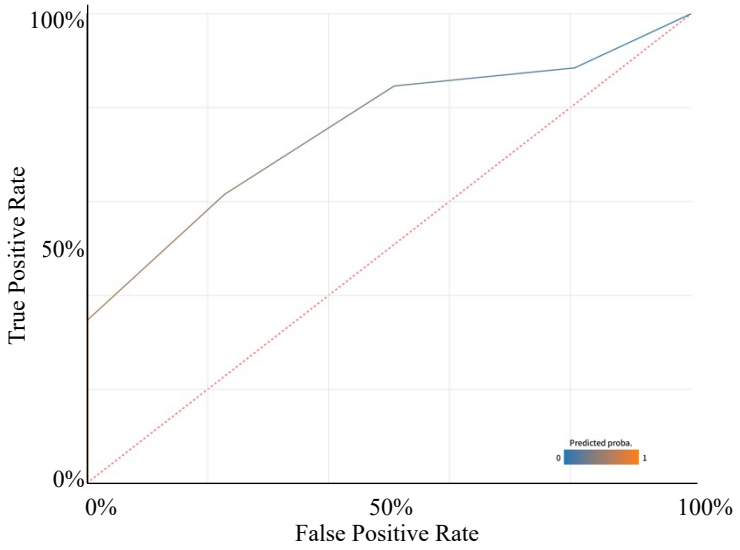

Figure 4-6 ROC graph of Decision Tree for 3-year PSR prediction

Table 4-8 Confusion matrix for decision tree 5-year PSR prediction

	Predicted Increase	Predicted Decrease	Total
Actually Increase	16	10	26
Actually Decrease	1	43	44
Total	17	53	70

Table 4-9 Decision tree performance metrics for 5-year PSR prediction

ROC–AUC Score	0.936
Accuracy	0.843
Precision	0.941
Recall	0.615
F1 Score	0.744

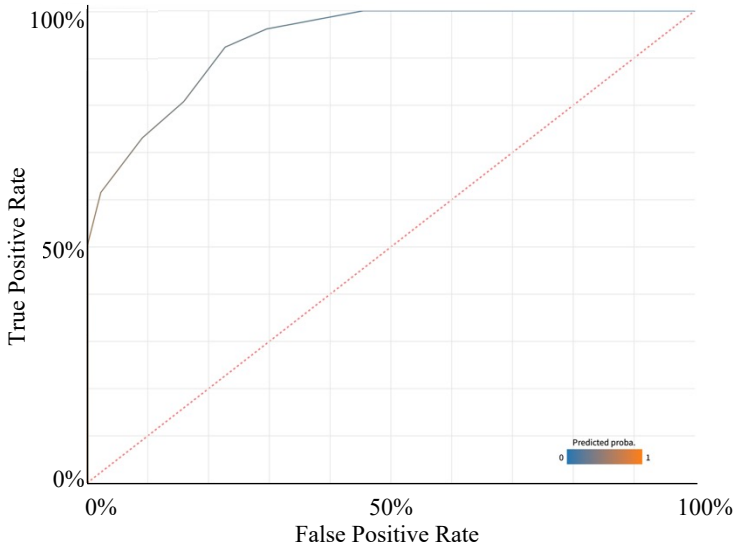

Figure 4-7 ROC graph of decision tree for 5-year PSR prediction

4.6 Hypothesis 4 Results

H4: *An SVM model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

This section includes the results of the SVM model. **Table 4-10** presents the confusion matrix for the 3-year model. **Table 4-11** demonstrates the performance metrics for the 3-year model against the test dataset. **Figures 4-8** exhibits the ROC chart for the 3-year model. **Tables 4-12** and **4-13** present the confusion matrix and performance metrics for the 5-year model, respectively. **Figure 4-9** displays the ROC chart for the 5-year model. A discussion of these results is presented in **Section 5.1.4**.

Table 4-10 Confusion matrix for SVM 3-year PSR prediction

	Predicted Increase	**Predicted Decrease**	**Total**
Actually Increase	17	9	26
Actually Decrease	17	6	57
Total	34	49	83

Table 4-11 SVM Performance metrics for 3-year PSR prediction

ROC–AUC Score	0.763
Accuracy	0.687
Precision	0.500
Recall	0.654
F1 Score	0.567

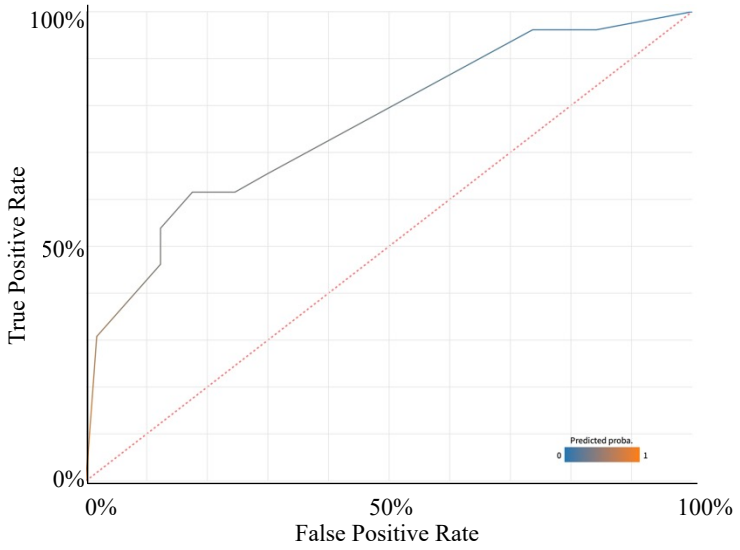

Figure 4-8 ROC graph of SVM for 3-year PSR prediction

Table 4-12 Confusion matrix for SVM 5-year PSR prediction

	Predicted Increase	**Predicted Decrease**	**Total**
Actually Increase	23	3	26
Actually Decrease	4	40	57
Total	27	43	70

Table 4-13 SVM performance metrics for 5-year PSR prediction

ROC–AUC Score	0.927
Accuracy	0.900
Precision	0.852
Recall	0.885
F1 Score	0.868

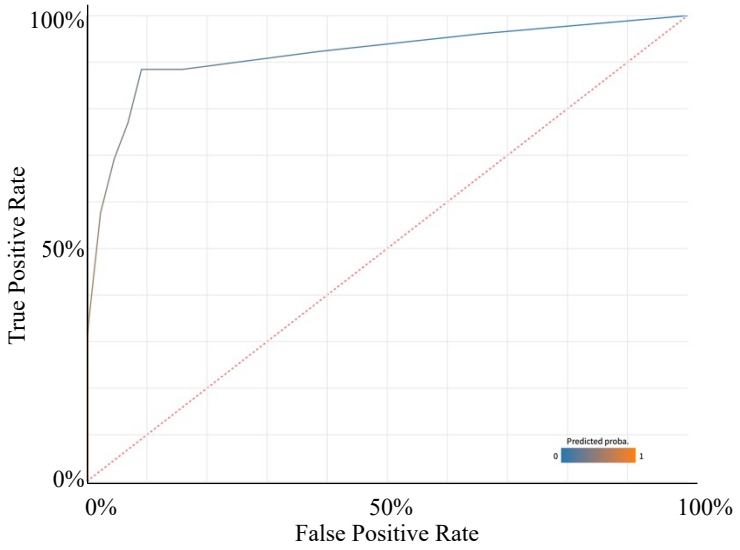

Figure 4-9 ROC graph of SVM for 5-year PSR prediction

4.7 Hypothesis 5 Results

H5: *A KNN model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

This section presents the results of the KNN ML model. **Table 4-14** illustrates the confusion matrix for the 3-year models. **Table 4-15** presents the performance metrics for the 3-year model against the test dataset. **Figure 4-10** shows the ROC chart for the 3-year

model. **Tables 4-16** and **4-17** present the confusion matrix and performance metrics for the 5-year model, respectively. **Figure 4-11** shows the ROC chart for the 5-year model. A discussion of these results is offered in **Section 5.1.5**.

Table 4-14 Confusion matrix for KNN 3-year PSR prediction

	Predicted Increase	**Predicted Decrease**	**Total**
Actually Increase	19	7	26
Actually Decrease	23	34	57
Total	42	41	83

Table 4-15 KNN performance metrics for 3-year PSR prediction

ROC–AUC Score	0.730
Accuracy	0.639
Precision	0.452
Recall	0.731
F1 Score	0.559

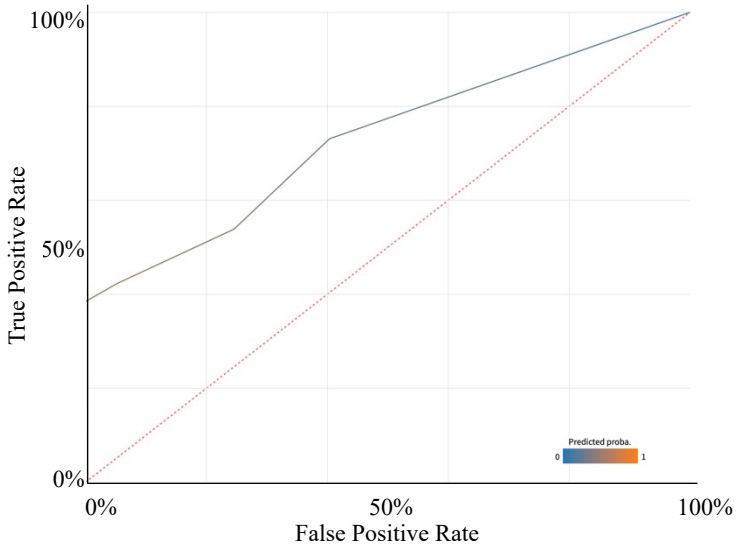

Figure 4-10 ROC graph of KNN for 3-year PSR Prediction

Table 4-16 Confusion matrix for KNN 5-year PSR prediction

	Predicted Increase	**Predicted Decrease**	**Total**
Actually Increase	22	4	26
Actually Decrease	3	41	44
Total	25	45	70

Table 4-17 KNN performance metrics for 5-year PSR prediction

ROC–AUC Score	0.935
Accuracy	0.900
Precision	0.880
Recall	0.846
F1 Score	0.863

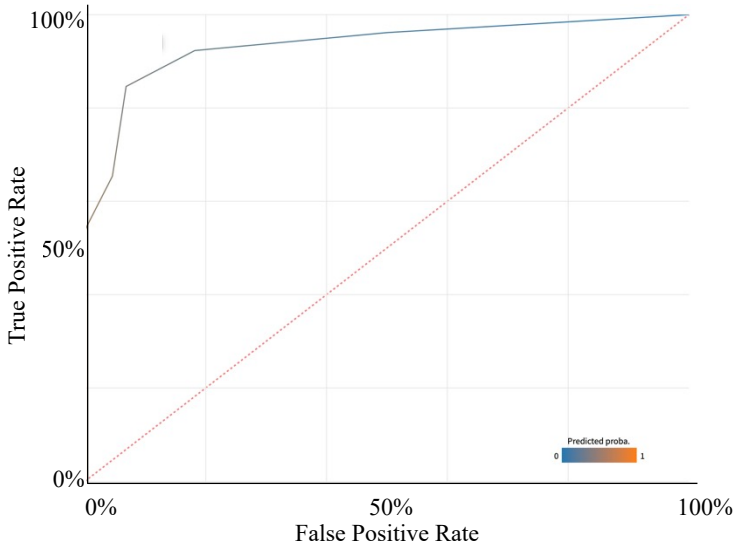

Figure 4-11 ROC graph of KNN for 5-year PSR prediction

4.8 Hypothesis 6 Results

H6: *A neural network model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

This section covers the results of the neural network ML model. **Table 4-18** shows the confusion matrix for the 3-year models. **Table 4-19** presents the performance

metrics for the 3-year model against the test dataset. **Figure 4-12** shows the ROC chart for the 3-year model. **Tables 4-20** and **4-21** present the confusion matrix and performance metrics for the 5-year model, respectively. **Figure 4-13** shows the ROC chart for the 5-year model. A discussion of these results is presented in **Section 5.1.6**.

Table 4-18 Confusion matrix for neural network 3-year PSR prediction

	Predicted Increase	**Predicted Decrease**	**Total**
Actually Increase	15	11	26
Actually Decrease	14	43	57
Total	29	54	83

Table 4-19 Neural network performance metrics for 3-year PSR prediction

ROC–AUC Score	0.710
Accuracy	0.699
Precision	0.517
Recall	0.577
F1 Score	0.545

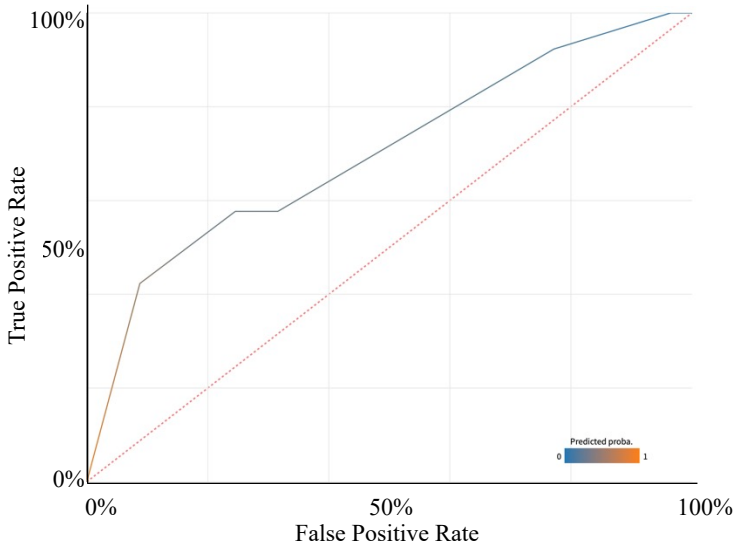

Figure 4-12 ROC graph of neural network for 3-year PSR Prediction

Table 4-20 Confusion matrix for neural network 5-year PSR prediction

	Predicted Increase	**Predicted Decrease**	**Total**
Actually Increase	22	4	26
Actually Decrease	5	39	44
Total	27	43	70

Table 4-21 Neural Network performance metrics for 5-year PSR prediction

ROC–AUC Score	0.952
Accuracy	0.871
Precision	0.815
Recall	0.846
F1 Score	0.830

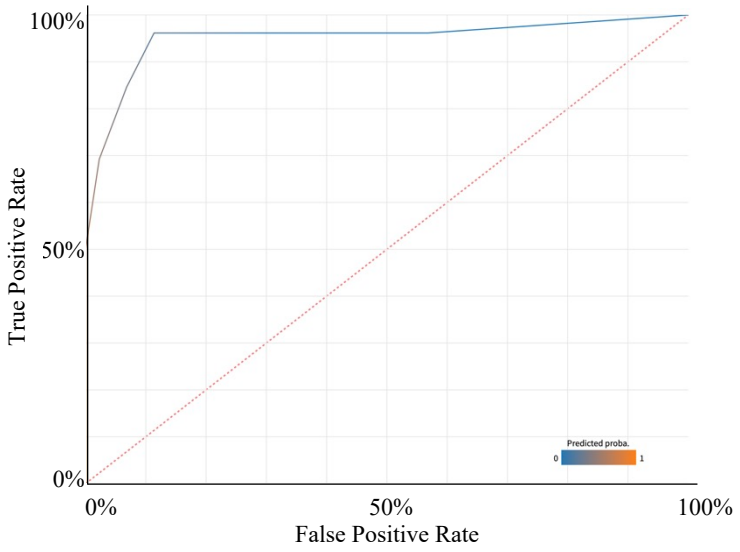

Figure 4-13 ROC graph of neural network for 5-year PSR prediction

4.9 Hypothesis 7 Results

H7: *A random forest model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

This section presents the results of the random forest ML model. **Table 4-22** shows the confusion matrix for the 3-year models. **Table 4-23** presents the performance metrics for the 3-year model against the test dataset. **Figure 4-14** displays the ROC chart for the 3-year model. **Tables 4-24** and **4-25** present the confusion matrix and performance metrics for the 5-year model, respectively. **Figure 4-15** illustrates the ROC chart for the 5-year model. A discussion of these results is presented in **Section 5.1.7**.

Table 4-22 Confusion matrix for random forest 3-year PSR prediction

	Predicted Increase	Predicted Decrease	Total
Actually Increase	21	5	26
Actually Decrease	26	31	57
Total	47	36	83

Table 4-23 Random forest performance metrics for 3-year PSR prediction

ROC–AUC Score	0.789
Accuracy	0.627
Precision	0.447
Recall	0.808
F1 Score	0.575

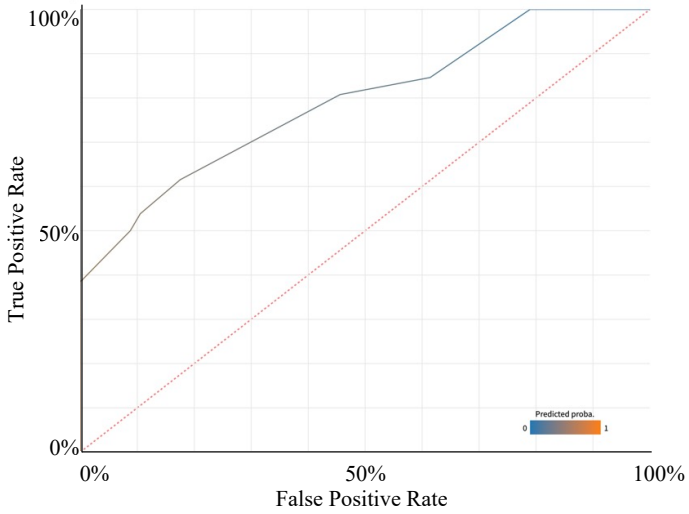

Figure 4-14 ROC graph of Random Forest for 3-year PSR prediction

Table 4-24 Confusion matrix for Random Forest 5-year PSR prediction

	Predicted Increase	Predicted Decrease	Total
Actually Increase	18	8	26
Actually Decrease	2	42	44
Total	26	44	70

Table 4-25 Random Forest performance metrics for 5-year PSR prediction

ROC–AUC Score	0.960
Accuracy	0.857
Precision	0.900
Recall	0.692
F1 Score	0.783

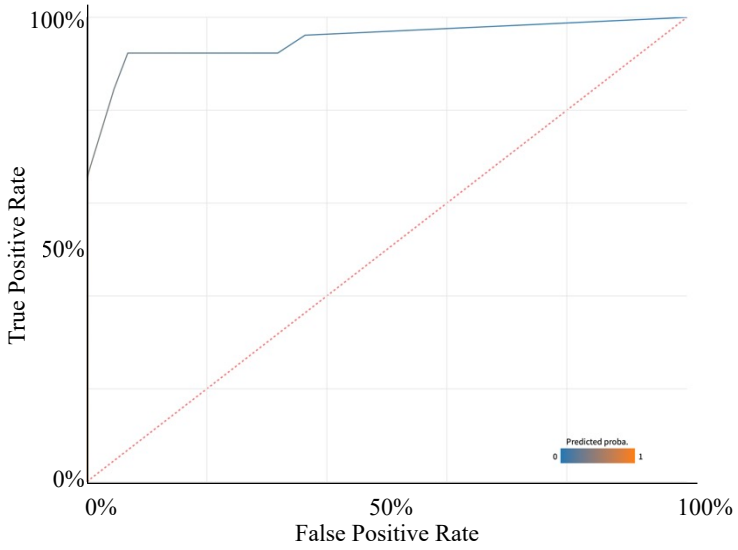

Figure 4-15 ROC graph of Random Forest for 5-year PSR prediction

4.10 Hypothesis 8 Results

H8: *A boosting ML model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

This section covers the results of the boosting ML model. **Table 4-26** presents the confusion matrix for the 3-year model. **Table 4-27** includes the performance metrics for the model against the 3-year test dataset. **Figure 4-16** displays the ROC chart for the 3-year model. **Tables 4-28** and **4-29** present the confusion matrix and performance metrics for the 5-year model, respectively. **Figure 4-17** shows the ROC chart for the 5-year model. A discussion of these results is given in **Section 5.1.8**.

Table 4-26 Confusion matrix for boosting 3-year PSR prediction

	Predicted Increase	Predicted Decrease	Total
Actually Increase	21	5	26
Actually Decrease	27	30	57
Total	48	35	83

Table 4-27 Boosting performance metrics for 3-year PSR prediction

ROC–AUC Score	0.751
Accuracy	0.614
Precision	0.438
Recall	0.808
F1 Score	0.568

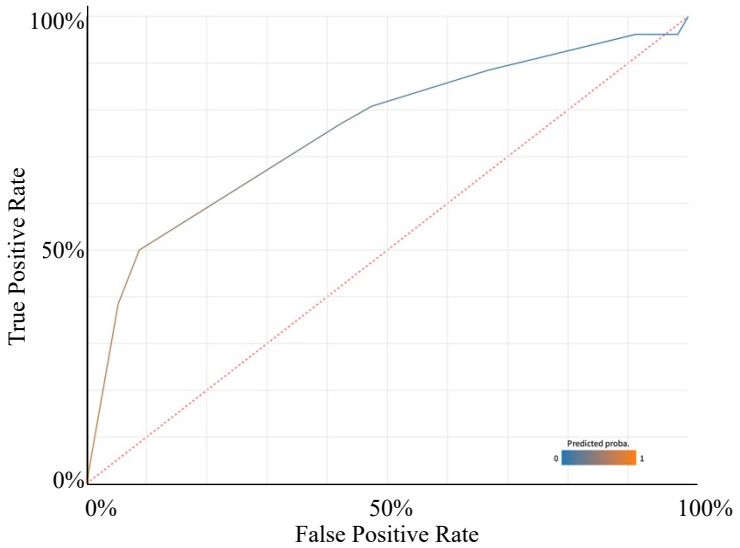

Figure 4-16 ROC graph of boosting for 3-year PSR Prediction

Table 4-28 Confusion matrix for Boosting 5-year PSR prediction

	Predicted Increase	Predicted Decrease	Total
Actually Increase	21	5	26
Actually Decrease	5	39	44
Total	26	44	70

Table 4-29 Boosting performance metrics for 3-year PSR prediction

ROC–AUC Score	0.913
Accuracy	0.857
Precision	0.808
Recall	0.808
F1 Score	0.808

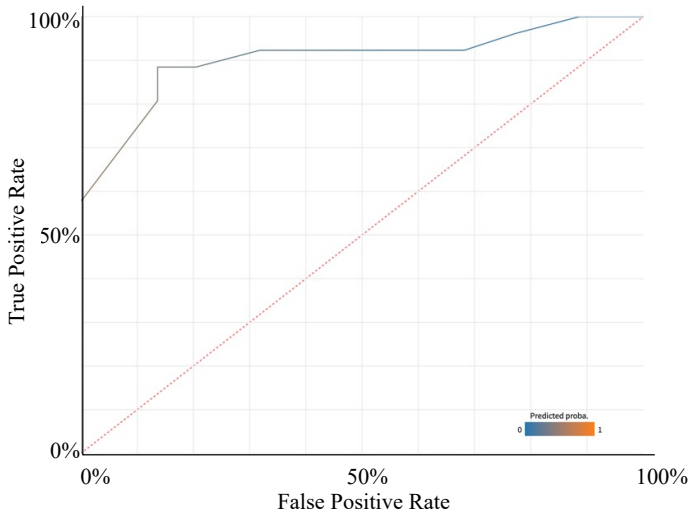

Figure 4-17 ROC graph of Boosting for 5-year PSR prediction

4.11 Hypothesis 9 Results

H9: *An ensemble averaging model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

This section covers the results of the ensemble averaging ML model. **Table 4-30** demonstrates the confusion matrix for the 3-year model. **Table 4-31** presents the performance metrics for the 3-year model against the test dataset. **Figure 4-18** exhibits the ROC chart for the 3-year model. **Tables 4-32** and **4-33** include the confusion matrix and performance metrics for the 5-year model, respectively. **Figure 4-19** displays the ROC chart for the 5-year model. A discussion of these results is presented in **Section 5.1.9**.

Table 4-30 Confusion matrix for ensemble averaging 3-year PSR prediction

	Predicted Increase	**Predicted Decrease**	**Total**
Actually Increase	11	15	26
Actually Decrease	1	56	57
Total	12	71	83

Table 4-31 Ensemble averaging performance metrics for 3-year PSR prediction

ROC–AUC Score	0.785
Accuracy	0.807
Precision	0.917
Recall	0.423
F1 Score	0.579

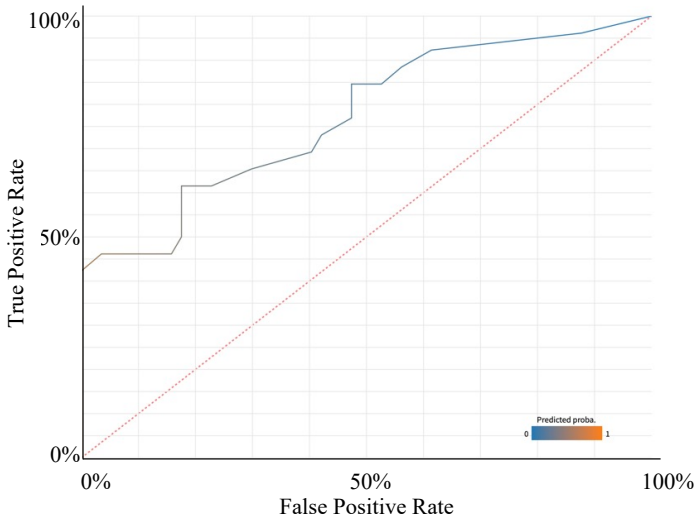

Figure 4-18 ROC graph of ensemble averaging for 3-year PSR prediction

Table 4-32 Confusion matrix for ensemble averaging 5-year PSR prediction

	Predicted Increase	**Predicted Decrease**	**Total**
Actually Increase	23	2	25
Actually Decrease	6	38	44
Total	29	40	69

Table 4-33 Ensemble averaging performance metrics for 3-year PSR prediction

ROC–AUC Score	0.964
Accuracy	0.884
Precision	0.793
Recall	0.920
F1 Score	0.852

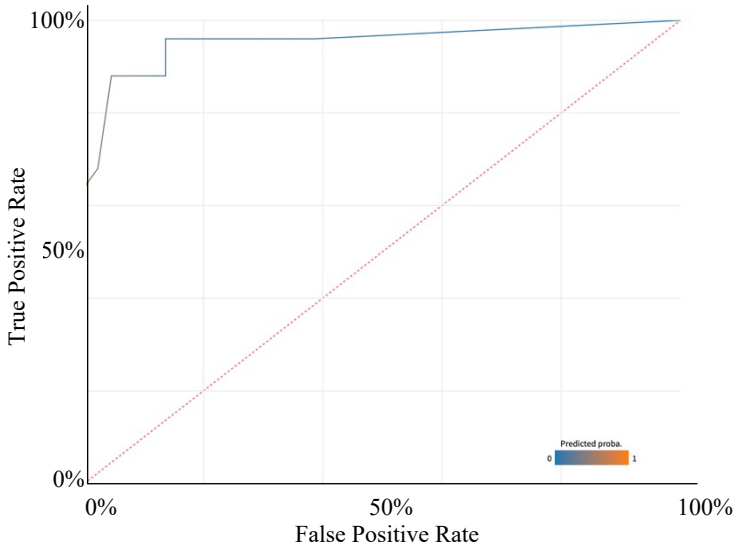

Figure 4-19 ROC graph of ensemble averaging for 5-year PSR prediction

4.12 Model Validation

4.12.1 Naive Bayes Validation Results

The dataset for the models was split into 20% test data and 80% training and validation. The results of the test data were presented in **Section 4-4**. For the training/validation dataset, 5-fold cross-validation was used to validate the training of the model, ensuring the model was not overfitting the data. **Tables 4-34** and **4-35** show the

range of performance metrics from the 5-fold testing on the 3-year and 5-year models, respectively. **Figures 4-20** and **4-21** show the ROC curves for the corresponding models. The results of the naïve Bayes model suggest that the model delivers consistent results, does not show overfitting, and provides sufficient validation.

Table 4-34 Naïve Bayes validation metrics for 3-year PSR prediction

ROC – AUC Score	4.21 (± 0.0830)
Accuracy	0.563 (± 0.0996)

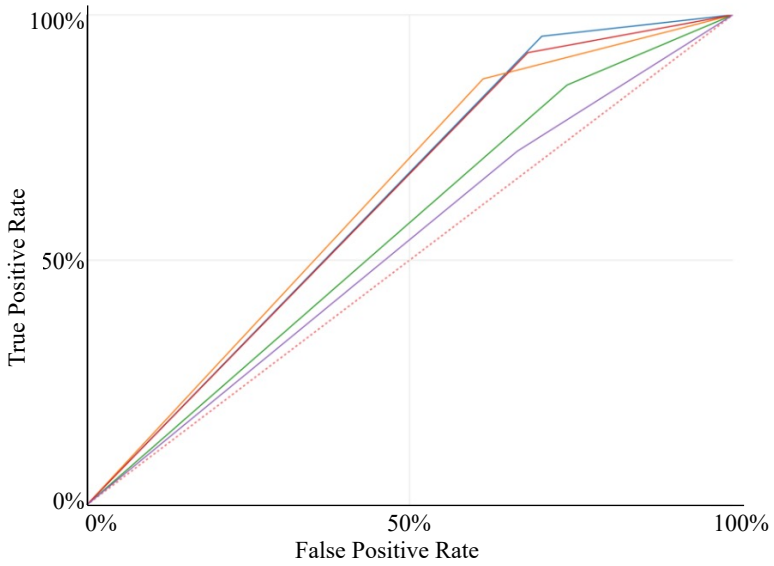

Figure 4-20 ROC graph of each fold of the 5-fold cross-validation for the Naïve Bayes model of 3-year PSR Prediction

Table 4-35 Naïve Bayes validation metrics for 5-year PSR prediction

ROC – AUC Score	0.694 (± 0.0902)
Accuracy	0.629 (± 0.102)

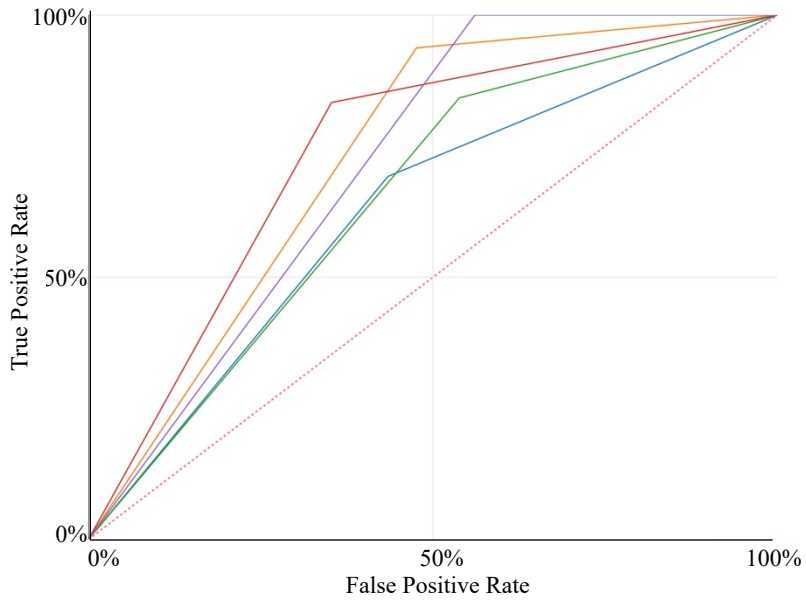

Figure 4-21 ROC graph of each fold of the 5-fold cross-validation for the Naïve Bayes model of 5-year PSR prediction

4.12.2 Decision Tree Validation Results

The dataset for the models was divided into 20% test data and 80% training and validation. The results of the test data were given in **Section 4-5**. For the training/validation dataset, 5-fold cross-validation was utilized to validate the training of the model. **Tables 4-36** and **4-37** demonstrate the range of performance metrics from the 5-fold testing on the 3-year and 5-year models respectively. **Figures 4-22** and **4-23** display the ROC curves for the corresponding models. The results of the Data Tree model suggest that the model delivers consistent results, does not show overfitting, and provides sufficient validation.

Table 4-36 Decision tree validation metrics for 3-year PSR prediction

ROC–AUC Score	0.787 (± 0.0509)
Accuracy	0.719 (± 0.0895)

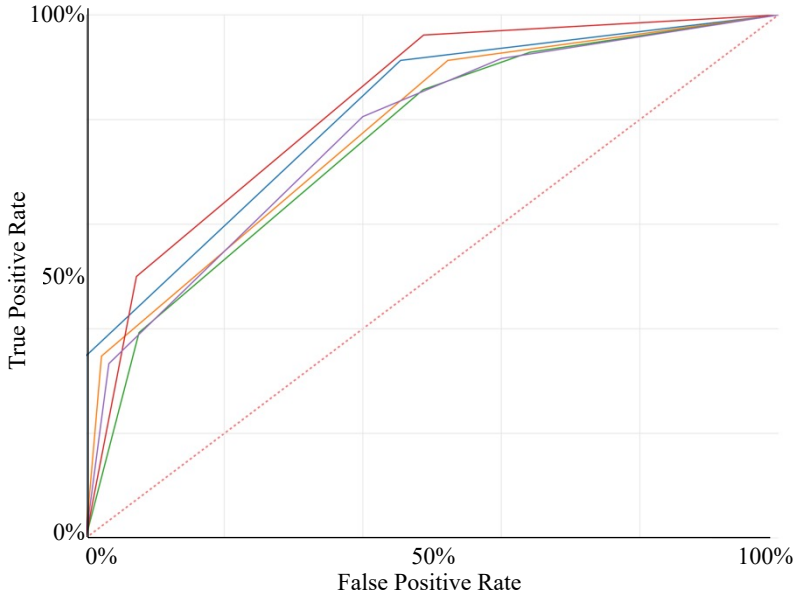

Figure 4-22 ROC graph of each fold of the 5-fold cross-validation for the Decision Tree model of 3-year PSR prediction

Table 4-37 Decision Tree validation metrics for 5-year PSR prediction

ROC–AUC Score	0.835 (± 0.0698)
Accuracy	0.798 (± 0.0822)

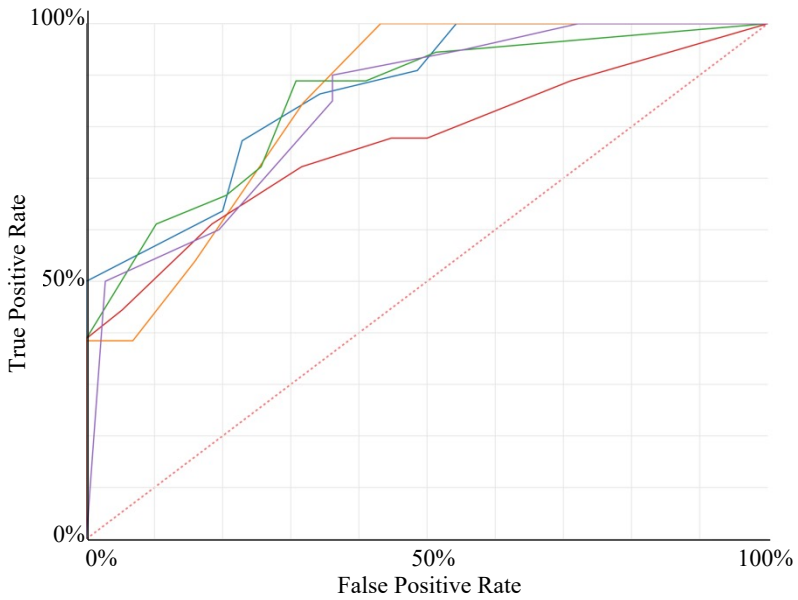

Figure 4-23 ROC graph of each fold of the 5-fold cross-validation for the Decision Tree model of 5-year PSR prediction

4.12.3 Support Vector Machine Validation Results

The dataset for the models was split into 20% test data and 80% training and validation. The results of the test data were presented in **Section 4-6**. For the training/validation dataset, 5-fold cross-validation was used to validate the training of the model. **Tables 4-38** and **4-39** show the range of performance metrics from the 5-fold testing on the 3-year and 5-year models respectively. **Figures 4-24** and **4-25** show the ROC curves for the corresponding models. The results of the SVM model suggest that the model delivers consistent results, does not show overfitting, and provides sufficient validation.

Table 4-38 SVM validation metrics for 3-year PSR prediction

ROC–AUC Score	0.878 (± 0.0621)
Accuracy	0.739 (± 0.113)

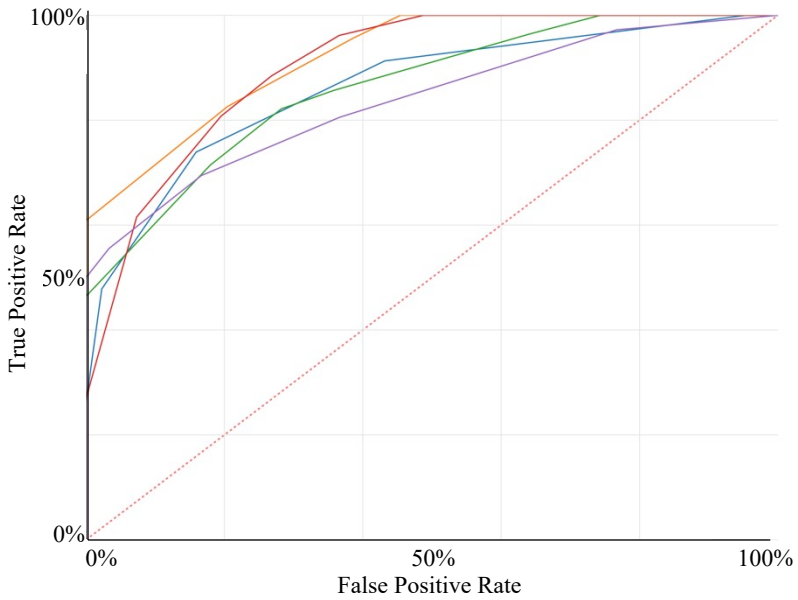

Figure 4-24 ROC graph of each fold of the 5-fold cross-validation for the SVM model of 3-year PSR Prediction

Table 4-39 SVM validation metrics for 5-year PSR prediction

ROC–AUC Score	0.900 (± 0.0614)
Accuracy	0.851 (± 0.104)

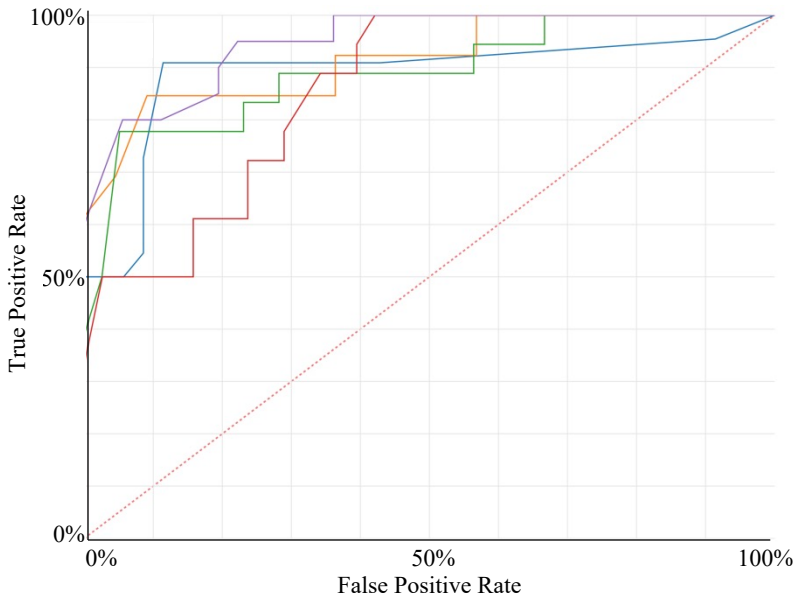

Figure 4-25 ROC graph showing the results of each fold of the 5-fold cross-validation used on the training data for the SVM model of 5-year PSR prediction

4.12.4 K-Nearest Neighbor Validation Results

The dataset for the models was divided into 20% test data and 80% training and validation. The results of the test data were given in **Section 4-7**. For the training/validation dataset, 5-fold cross-validation was employed to validate the training of the model. **Tables 4-40** and **4-41** present the range of performance metrics from the 5-fold testing on the 3-year and 5-year models respectively. **Figures 4-24** and **4-25** demonstrate the ROC curves for the corresponding models. The results of the KNN model suggest that the model delivers consistent results, does not show overfitting, and provides sufficient validation.

Table 4-40 KNN validation metrics for 3-year PSR prediction

ROC – AUC Score	4.27 (± 0.0685)
Accuracy	0.760 (± 0.144)

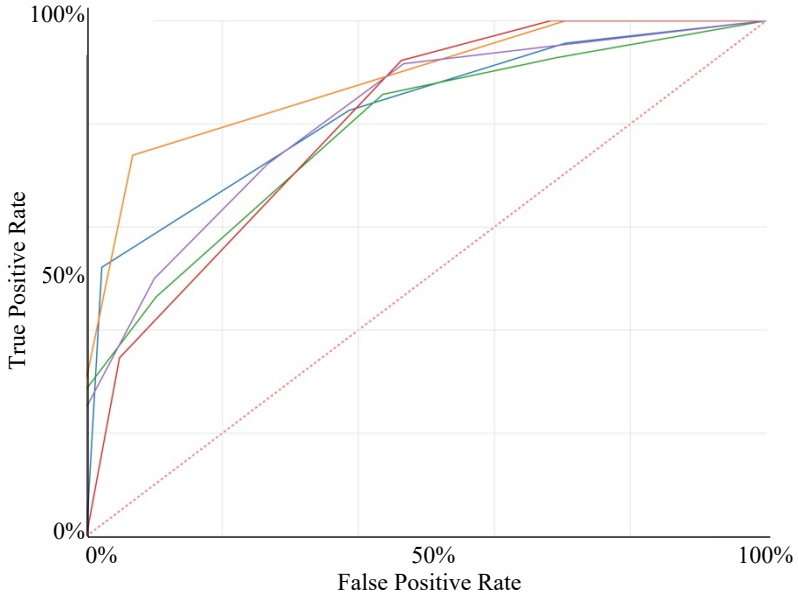

Figure 4-26 ROC graph of each fold of the 5-fold cross-validation for the KNN model of 3-year PSR prediction

Table 4-41 KNN validation metrics for 5-year PSR prediction

ROC – AUC Score	0.837 (± 0.115)
Accuracy	0.820 (± 0.0542)

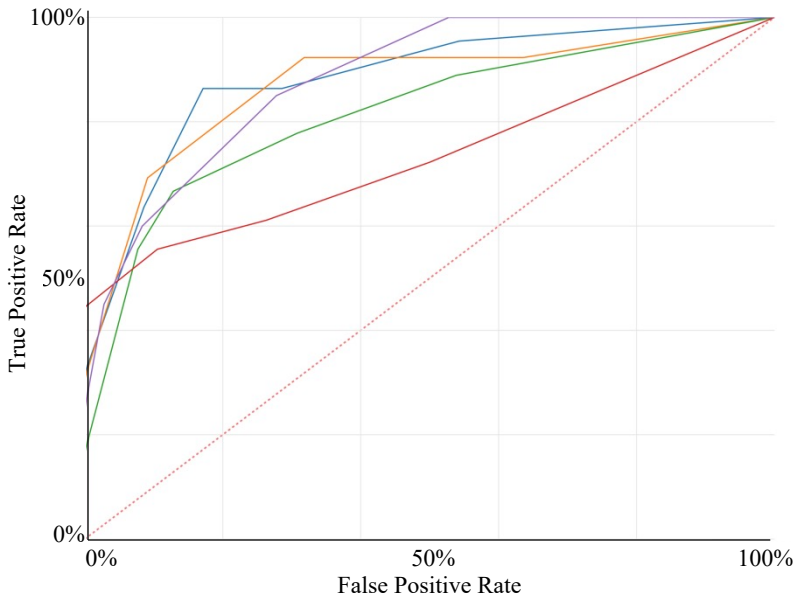

Figure 4-27 ROC graph of each fold of the 5-fold cross-validation for the KNN model of 3-year PSR prediction

4.12.5 Neural Network Validation Results

The dataset for the models was split into 20% test data and 80% training and validation. The results of the test data were presented in **Section 4-8**. For the training/validation dataset, 5-fold cross-validation was used to validate the training of the model. **Tables 4-42** and **4-43** show the range of performance metrics from the 5-fold testing on the 3-year and 5-year models respectively. **Figures 4-26** and **4-27** illustrate the ROC curves for the corresponding models. The results of the neural network model suggest that the model delivers consistent results, does not show overfitting, and provides sufficient validation.

Table 4-42 Neural network validation metrics for 3-year PSR prediction

ROC–AUC Score	0.825 (± 0.0847)
Accuracy	0.775 (± 0.0775)

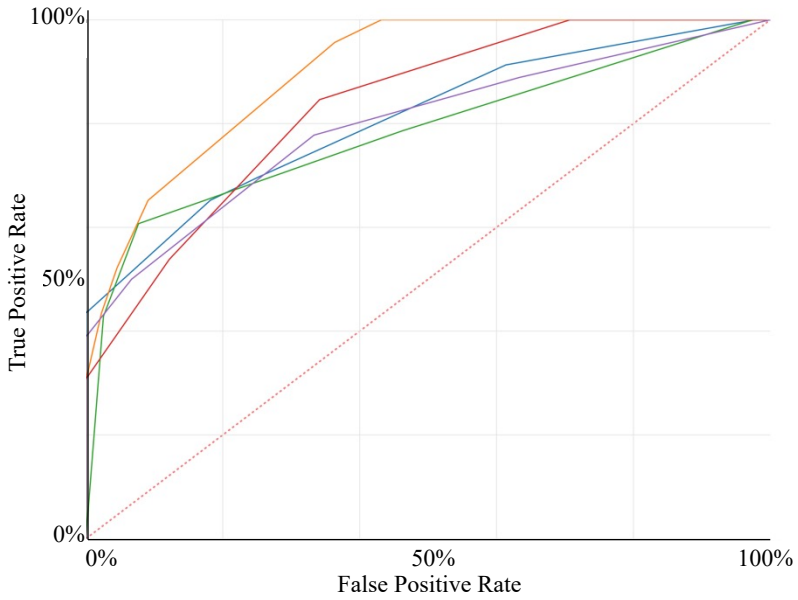

Figure 4-28 ROC graph of each fold of the 5-fold cross-validation for the KNN model of 3-year PSR Prediction

Table 4-43 Neural Network validation metrics for 5-year PSR prediction

ROC–AUC Score	0.867 (± 0.0851)
Accuracy	0.820 (± 0.105)

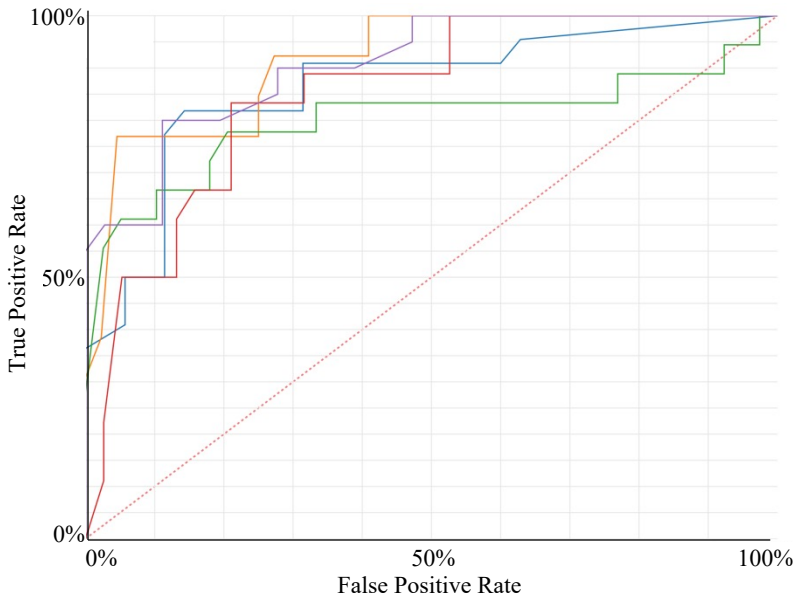

Figure 4-29 ROC graph of each fold of the 5-fold cross-validation for the KNN model of 5-year PSR prediction

4.12.6 Random Forest Validation Results

The dataset for the models was split into 20% test data and 80% training and validation. The results of the test data were presented in **Section 4-9**. For the training/validation dataset, 5-fold cross-validation was used to validate the training of the model. **Tables 4-44** and **4-45** show the range of performance metrics from the 5-fold testing on the 3-year and 5-year models respectively. **Figures 4-28** and **4-29** show the ROC curves for the corresponding models. The results of the Random Forest model suggest that the model delivers consistent results, does not show overfitting, and provides sufficient validation.

Table 4-44 Random Forest validation metrics for 3-year PSR prediction

ROC–AUC Score	0.909 (± 0.0640)
Accuracy	0.820 (± 0.122)

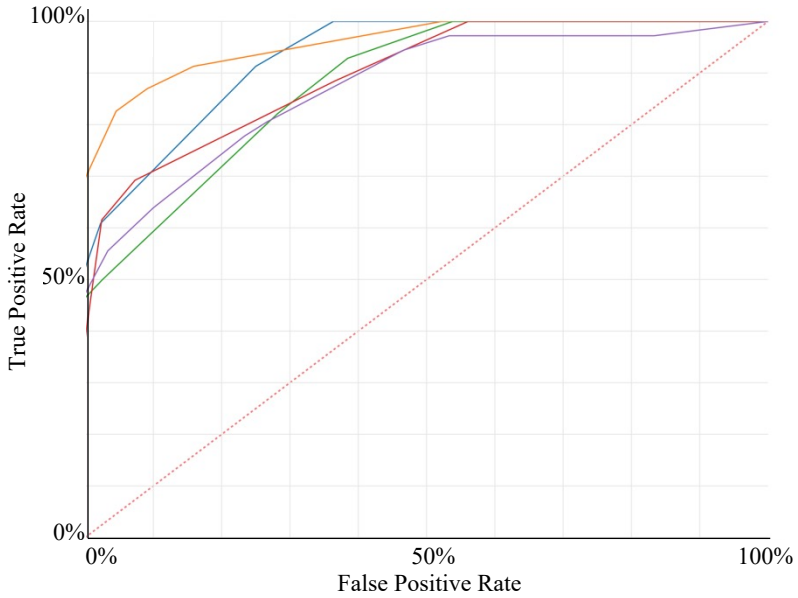

Figure 4-30 ROC graph of each fold of the 5-fold cross-validation for the Random Forest model of 3-year PSR Prediction

Table 4-45 Random Forest validation metrics for 5-year PSR prediction

ROC–AUC Score	0.932 (± 0.0565)
Accuracy	0.894 (± 0.0805)

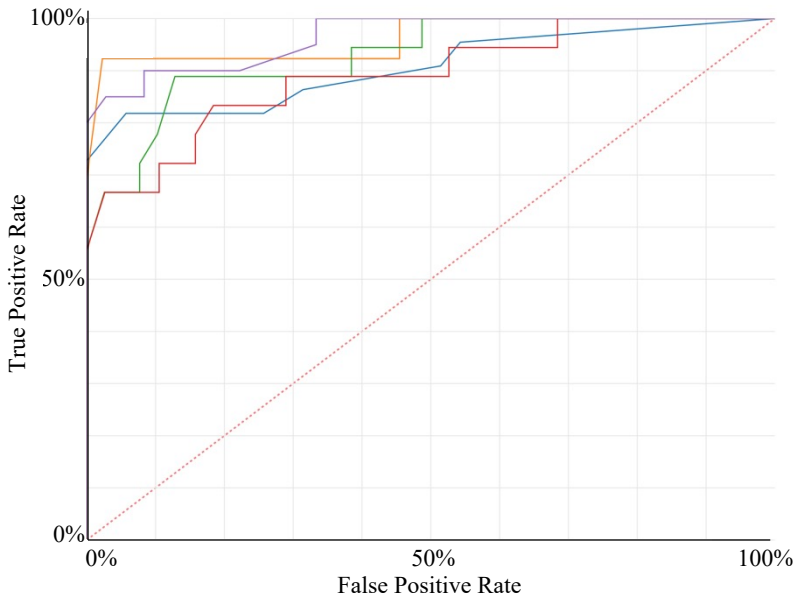

Figure 4-31 ROC graph of each fold of the 5-fold cross-validation for the Random Forest model of 5-year PSR prediction

4.12.7 Boosting Validation Results

The dataset for the models was split into 20% test data and 80% training and validation. The results of the test data were presented in **Section 4-10**. For the training/validation dataset, 5-fold cross-validation was used to validate the training of the model. **Tables 4-46** and **4-47** show the range of performance metrics from the 5-fold testing on the 3-year and 5-year models respectively. **Figures 4-30** and **4-31** show the ROC curves for the corresponding models. The results of the boosting model suggest that the model delivers consistent results, does not show overfitting, and provides sufficient validation.

Table 4-46 Boosting validation metrics for 3-year PSR prediction

ROC–AUC Score	0.835 (± 0.0511)
Accuracy	0.751 (± 0.0645)

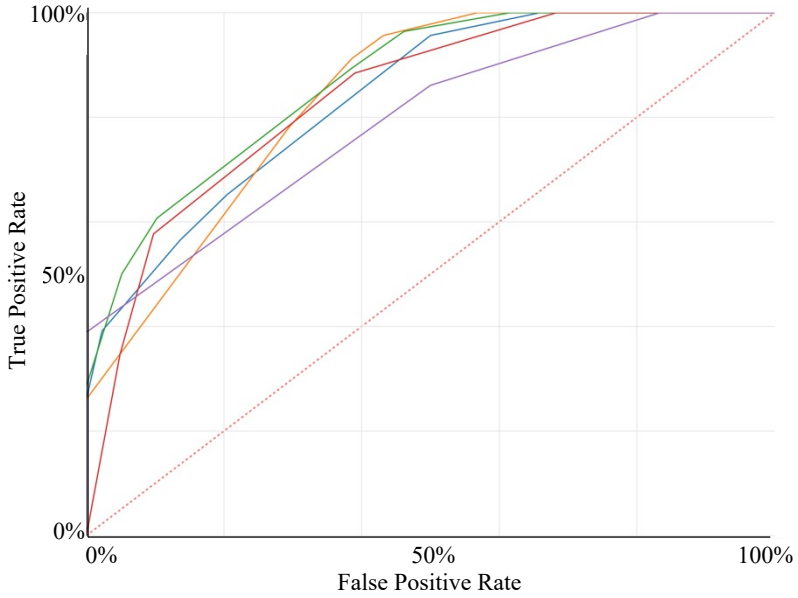

Figure 4-32 ROC graph of each fold of the 5-fold cross-validation for the boosting model of 3-year PSR prediction

Table 4-47 Boosting validation metrics for 5-year PSR prediction

ROC–AUC Score	0.890 (± 0.0820)
Accuracy	0.802 (± 0.0257)

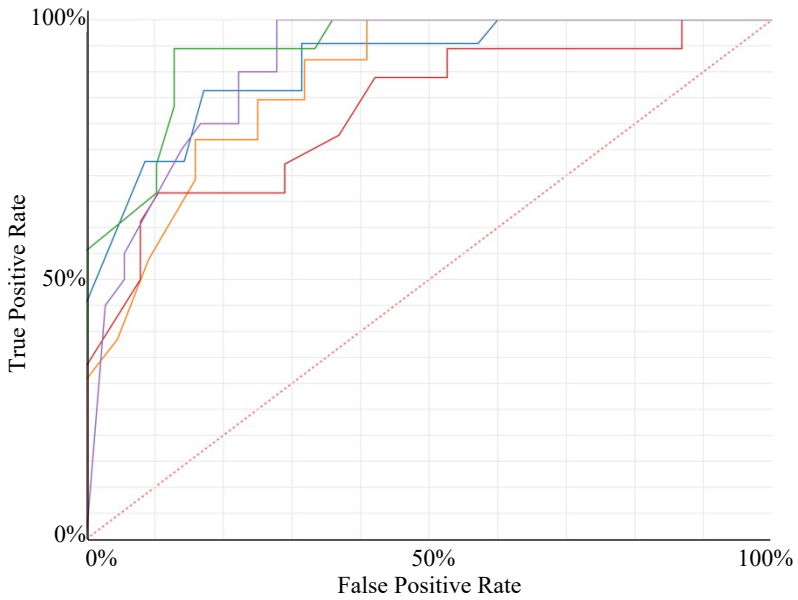

Figure 4-33 ROC graph of each fold of the 5-fold cross-validation for the boosting model of 3-year PSR prediction

4.12.8 Ensemble Averaging Validation Results

The dataset for the ensemble models was split into 60% training, 20% validation, and 20% test data. The results of the test data were presented in **Section 4-11**. **Tables 4-44** and **4-45** show performance metrics for the 3-year and 5-year models respectively. **Figures 4-28** and **4-29** show the ROC curves for the corresponding models. The metrics for the validation model are consistent with the test dataset metrics, indicating a valid model without overfitting.

Table 4-48 Ensemble averaging validation metrics for 3-year PSR prediction

ROC–AUC Score	0.710
Accuracy	0.786

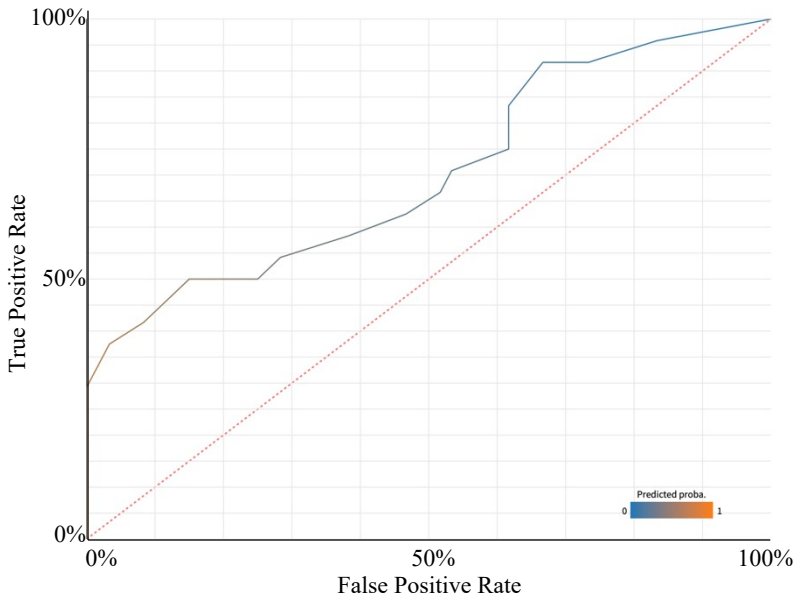

Figure 4-34 ROC graph of the validation set used for the ensemble averaging model of 3-year PSR prediction

Table 4-49 Ensemble averaging validation metrics for 5-year PSR prediction

ROC–AUC Score	0.923
Accuracy	0.894

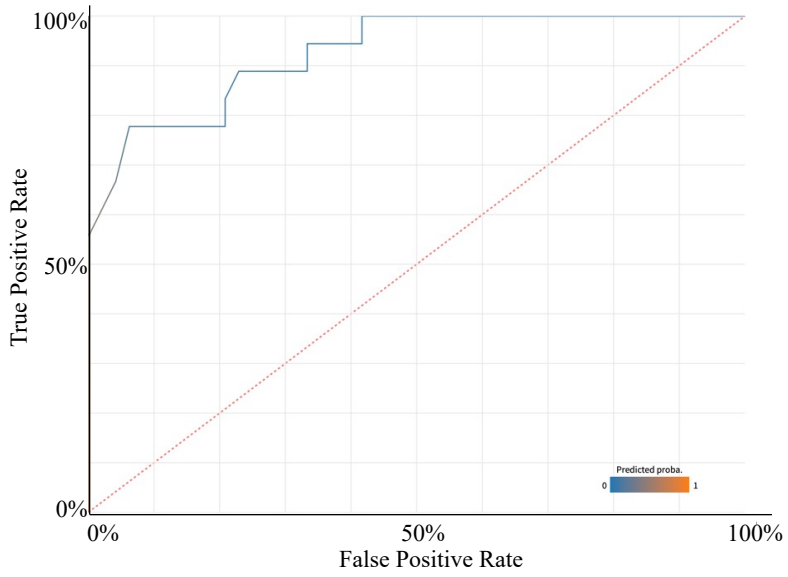

Figure 4-35 ROC graph of the validation set used for the ensemble averaging model of 3-year PSR prediction

4.13 Summary of Model Metrics

For comparison purposes, the results of the ML metrics are shown by model type in a consolidated format. The training feature was unbalanced; thus, the accuracy metric alone was not a good indicator of overall model performance. **Table 4-50** shows the results for all metrics of the 3-year model, and **Table 4-51** shows the 5-year model results. **Section 5.1.10** discusses the comparison analysis.

Table 4-50 ML Metrics for the 3-year model performance by model type

3-Year	Naive Bayes	Decision TREE	SVM	KNN	Neural Network	Random Forest	Boosting	Ensemble averaging
ROC–AUC Score	0.514	0.755	0.763	0.730	0.710	0.789	0.751	0.785
Accuracy	0.361	0.602	0.687	0.639	0.699	0.627	0.614	0.807
Precision	0.320	0.431	0.500	0.452	0.517	0.447	0.438	0.917
Recall	0.923	0.846	0.654	0.731	0.577	0.808	0.808	0.423
F1 Score	0.475	0.571	0.567	0.559	0.545	0.575	0.568	0.579

Table 4-51 ML Metrics for the 5-year model performance by model type

5-Year	Naïve Bayes	Decision Tree	SVM	KNN	Neural Network	Random Forest	Boosting	Ensemble averaging
ROC–AUC Score	0.724	0.936	0.927	0.935	0.952	0.960	0.913	0.964
Accuracy	0.657	0.843	0.900	0.900	0.871	0.857	0.857	0.884
Precision	0.523	0.941	0.852	0.880	0.815	0.900	0.808	0.793
Recall	0.885	0.615	0.885	0.846	0.846	0.692	0.808	0.920
F1 Score	0.657	0.744	0.868	0.863	0.830	0.783	0.808	0.852

Discussion and Conclusions

5.1 Discussion

The goal of this research was to determine whether machine learning (ML) techniques could be used to predict innovation outcomes from acquisitions within the aerospace and defense industry. Previous research has identified, developed, and used different methods to measure innovation, including using ML (Forner et al., 2019). Researchers have used ML to predict acquisition outcomes (Ross et al., 2021). Little research has combined ML with innovation outcomes for acquisitions, regardless of industry.

The remainder of this chapter discusses the results of the hypotheses outlined in Chapter 1 as well as the derived research questions. The results of the hypotheses and analysis outputs from Chapter 4 are discussed in **Sections 5.1.1** to **5.1.9**. **Section 5.2**. contains the conclusion and lessons learned. **Section 5.3** presents how this research contributes to the current body of knowledge. Finally, **Section 5.4** provides recommendations for future research to provide additional knowledge on the topics covered.

5.1.1 Discussion of Hypothesis 1

H1: *Startup acquisitions are associated with a statistically significant increase in the patent success ratio (PSR) of the acquiring company post-acquisition.*

Hypothesis 1 was tested by analyzing 571 acquisitions that took place from 1995 to 2017 for 34 different US defense contractors. The results presented in **Section 4.3** suggest that the number of acquisitions was not a statistically significant (p-value = 0.462) driver affecting the PSR of the acquiring company. The results indicate that the

year the acquisition occurred was a statistically significant indicator of PSR, with a *p*-value of less than 0.001. The coefficient of determination had a value of 0.452 which indicates that the regression was a poor fit. The year might have been statistically significant due to a growing gap in innovation between defense companies relative to all other companies seeking patents.

Result: Hypothesis not confirmed.

5.1.2 Discussion of Hypothesis 2

H2: *A naïve Bayes network can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

Hypothesis 2 was tested using two different models and datasets. The first dataset, used to analyze the 3-year increase in PSR, consisted of 417 acquisitions by defense companies from 1995 to 2017 for 34 different US defense contractors. The second dataset consisted of 353 defense acquisitions from 1999 to 2014. The 3-year PSR prediction model had an accuracy of 36.1% and a receiver operating characteristic (ROC)–area under curve (AUC) score of 51.4% (**Table 4-3**), indicating that this model could not successfully provide a reliable prediction for PSR changes. As shown in **Table 4-5,** the 5-year PSR prediction achieved an accuracy of 65.7% and a ROC–AUC score of 72.4%, implying that this model could not successfully provide a reliable prediction for 5-year PSR changes either.

3-year Model Result: Hypothesis not confirmed.

5-year Model Result: Hypothesis not confirmed.

5.1.3 Discussion of Hypothesis 3

H3: *A decision tree model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

Two different models and datasets were used to test Hypothesis 3. The first dataset, used to analyze the 3-year increase in PSR, consisted of 417 acquisitions by defense companies from 1995 to 2017 for 34 different US defense contractors. The second dataset consisted of 353 defense acquisitions from 1999 to 2014. **Table 4-7** shows that the accuracy of the 3-year PSR prediction was 60.2% and the ROC–AUC score was 75.5%, indicating that this model could not successfully provide a reliable prediction for PSR changes. **Table 4-9** shows an accuracy of 84.3% and a ROC–AUC score of 93.6% for the 5-year PSR prediction, indicating that this model successfully provided a reliable prediction for PSR changes for the 5-year prediction alone.

3-year Model Result: Hypothesis not confirmed.

5-year Model Result: Hypothesis confirmed.

5.1.4 Discussion of Hypothesis 4

H4: *A support vector machine (SVM) model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

Hypothesis 4 was examined using two different models and datasets. The first dataset, used to analyze the 3-year increase in PSR, consisted of 417 acquisitions by defense companies from 1995 to 2017 for 34 different US defense contractors. The second dataset included 353 defense acquisitions from 1999 to 2014. **Table 4-11** shows

an accuracy of 68.7% and a ROC–AUC score of 76.3% for the 3-year PSR prediction, indicating that this model could not successfully provide a reliable prediction for PSR changes. **Table 4-13** shows an accuracy of 90.0% and a ROC–AUC score of 92.7% for the 5-year PSR prediction, indicating that this model successfully provided a reliable prediction for 5-year PSR changes.

3-year Model Result: Hypothesis not confirmed.

5-year Model Result: Hypothesis confirmed.

5.1.5 Discussion of Hypothesis 5

H5: *A K-nearest neighbor (KNN) model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

Hypothesis 5 was tested using two different models and datasets. The first dataset was used to analyze the 3-year increase in PSR and consisted of 417 acquisitions by defense companies from 1995 to 2017 for 34 different US defense contractors. The second dataset consisted of 353 defense acquisitions from 1999 to 2014. The 3-year PSR prediction had an accuracy of 63.9% and a ROC–AUC score of 73.0% (**Table 4-15**), indicating that this model could not successfully provide a reliable prediction for PSR changes. The 5-year PSR prediction achieved an accuracy of 90.0% and a ROC–AUC score of 93.5% (**Table 4-17**), indicating that this model successfully provided a reliable prediction for 5-year PSR changes.

3-year Model Result: Hypothesis not confirmed.

5-year Model Result: Hypothesis confirmed.

5.1.6 Discussion of Hypothesis 6

H6: *A neural network model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

Hypothesis 6 was tested using two different models and datasets. The first dataset, used to analyze the 3-year increase in PSR, consisted of 417 acquisitions by defense companies from 1995 to 2017 for 34 different US defense contractors. The second dataset consisted of 353 defense acquisitions from 1999 to 2014. **Table 4-19** reveals an accuracy of 69.9% and a ROC–AUC score of 71.0% for the 3-year PSR prediction, indicating that this model could not successfully provide a reliable prediction for PSR changes. **Table 4-21** demonstrates an accuracy of 87.1% and a ROC–AUC score of 95.2% for the 5-year PSR prediction, indicating that this model successfully provided a reliable prediction for 5-year PSR changes.

3-year Model Result: Hypothesis not confirmed.

5-year Model Result: Hypothesis confirmed.

5.1.7 Discussion of Hypothesis 7

H7: *A random forest model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

Hypothesis 7 was tested using two different models and datasets. The first dataset, used to analyze the 3-year increase in PSR, included 417 acquisitions by defense companies from 1995 to 2017 for 34 different US defense contractors. The second dataset consisted of 353 defense acquisitions from 1999 to 2014. **Table 4-23** shows an accuracy

of 62.7% and a ROC–AUC score of 78.9% for the 3-year PSR prediction, indicating that this model could not successfully provide a reliable prediction for PSR changes. **Table 4-25** shows an accuracy of 85.7% and a ROC–AUC score of 96.0% for the 5-year PSR prediction, indicating that this model successfully provided a reliable prediction for PSR changes.

3-year Model Result: Hypothesis not confirmed.

5-year Model Result: Hypothesis confirmed.

5.1.8 Discussion of Hypothesis 8

H8: *A boosting validation results model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

Hypothesis 8 was tested using two different models and datasets. The first dataset consisted of 417 acquisitions by defense companies from 1995 to 2017 for 34 different US defense contractors and was used to analyze the 3-year increase in PSR. The second dataset consisted of 353 defense acquisitions from 1999 to 2014 and was used to analyze the 5-year increase in PSR. **Table 4-31** shows an accuracy of 61.4 and a ROC–AUC score of 75.1% for the 3-year PSR prediction, indicating that this model could not successfully provide a reliable prediction for PSR changes. **Table 4-33** shows an accuracy of 85.7% and a ROC–AUC score of 91.3% for the 5-year PSR prediction, indicating that this model successfully provided a reliable prediction for PSR changes.

3-year Model Result: Hypothesis not confirmed.

5-year Model Result: Hypothesis confirmed.

5.1.9 Discussion of Hypothesis 9

H9: *An ensemble averaging model can predict an average 3-year and 5-year increase to PSR for the acquiring company with an accuracy greater than 80% and an AUC greater than 80%.*

Hypothesis 9 was tested using two different models using different datasets. The first dataset, used to analyze the 3-year increase in PSR, consisted of 417 acquisitions by defense companies from 1995 to 2017 for 34 different US defense contractors. The second dataset consisted of 353 defense acquisitions from 1999 to 2014. **Table 4-31** shows an accuracy of 78.5% and a ROC–AUC score of 80.7% for the 3-year PSR prediction, indicating that this model could not successfully provide a reliable prediction for PSR changes. **Table 4-33** shows an accuracy of 88.4% and a ROC–AUC score of 96.4% for the 5-year PSR prediction, indicating that this model successfully provided a reliable prediction for PSR changes.

3-year Model Result: Hypothesis not confirmed.

5-year Model Result: Hypothesis confirmed.

5.1.10 Comparison of Models

Table 4-50 and **4-51** show the results of ML metrics for the 3-year and 5-year metrics respectively. Naïve Bayes had the lowest scores for ROC–AUC and accuracy for both the 3- and 5-year models, which was not unexpected from the experience of other researchers as outlined in **Section 2.3.2.1**. The single learning algorithms, decision tree, SVM, KNN, and neural networks, all performed better than naïve Bayes, across both time periods. While the ensemble models achieved the best results in the 3-year time frame. At 5 years, the ensemble models had comparable performance metrics to the

single learners, which was unexpected. Of the ensemble models, ensemble averaging performed the best, which is consistent with the literature outlined in **Section 2.3.2.9**.

5.2 Conclusions

This praxis research focused on answering the following questions outlined in Chapter 1 of this document:

RQ1: Does a relationship exist between startup acquisitions by defense contractors and an increased PSR at the acquiring company post-acquisition?

RQ2: How accurate are models developed to estimate PSR changes using startup acquisition attributes based on Accuracy and ROC–AUC?

Previous research suggests that increasing the number of startup acquisitions alone does not indicate that a defense company's overall innovative ability will increase. It is possible for some ML tools to successfully predict acquisitions that will increase innovation, both 3 years and 5 years after acquisition. Although, as shown in Chapter 2, a considerable body of research was devoted to innovation and startup success, a gap exists in the literature regarding combining those two items using ML techniques.

The increase or decrease of innovation for defense companies acquiring startups can be predicted using ML techniques. Although this praxis found a relationship between startup acquisition and defense innovation, that relationship is more complex than simply increasing innovation by purchasing more companies. This observation aligns with the data from Chapter 2, which described some factors that affect innovation within a company. Key conclusions of this praxis include:

1. Longer-term 5-year outcome predictions were more accurate than nearer, 3-year outcomes. The ability to predict over a longer period can likely be attributed to regression to the mean for innovation performance. Immediately after the acquisition, efforts spent to integrate the businesses can cause a decline in innovation (Trichterborn et al., 2016). Over time, the companies that can successfully integrate the businesses to achieve greater innovation will get consistent PSR results, but that integration time may vary by business.
2. Ensemble averaging models performed best in both accuracy and ROC–AUC than other methods. Several other models still performed well, some exceeding 80% accuracy and ROC–AUC on the 5-year prediction. As outlined in **Section 2.3.2.6.3**, ensemble models have been used to get superior performance over individual learners, such as naïve Bayes, when making mergers and acquisitions (M&A) predictions outside of innovation. This also was true for innovation prediction using PSR.
3. Acquisitions can have adverse effects on company performance outside of innovation considerations (Ma & Liu, 2016). Different types of companies achieve different results from M&A due to factors outside of acquisition count (Tobiassen & Pettersen, 2017). The results of Hypothesis 1 show that acquisitions alone are not statistically significant in predicting innovation outcomes, aligning with previous research.

5.2.1 Lessons Learned

This research found four key conclusions in researching ML models for predicting effects on innovation for defense acquisitions that will be useful for future researchers in the field:

1. The availability of quality data is the most important element for the models and drives which metrics to use for training. This research focused on publicly available, crowdsourced data to train the ML models. There are other measures of innovation that require non-publicly available data, such as the number of employees and other internal metrics, that can provide potentially more effective models.
2. Data preparation and cleaning are more important than the algorithms themselves, as the algorithms are relatively straightforward when the data is in order. Thought must be provided into how to get the data in a format that the algorithm can ingest to run. For example, there were multiple values in a single data field, which required data cleaning to make them ML-usable fields. There were also fields where >95% of the values were the same, so they required processing, but added no value to the results, and could even make the accuracy worse.
3. The algorithms used for the 3-year and 5-year ensemble models were developed with different sub-learners. The composition of learners for the ensemble model was not consistent or independent of year, a point that is important to consider when performing similar research.

4. Microsoft Excel is limited to 16 variables for multiple regression analysis. Although there were only three variable inputs, the company name input was a nominal variable with over 30 values. Dummy encoding was required for the multiple regression to accept the nominal variable, which caused the total number of input variables to exceed the 16-variable Excel input threshold (total values for nominal minus 1, plus the two other variables).

5.3 Contributions to Body of Knowledge

Previous research has studied methods for measuring innovation and other works have used ML to predict M&A outcomes. This praxis is the first to use both, making predictions using ML of the effect on innovation resulting from an acquisition.

The results showed that ML models can be developed to successfully predict innovation performance at both 3- and 5-year periods post acquisition. Those models were able to achieve over 80% accuracy for the 5 years post-acquisition. It also showed that for both 3- and 5- year measures, ensemble models were the most accurate for predicting innovation performance. This information can be used by organizations to understand how to be more successful in acquiring startups to improve their overall innovation.

5.4 Recommendations for Future Research

To advance knowledge in this area, four recommendations can be made:

1. The focus of this research was on US-based defense companies and the models developed in this research may not apply internationally. Further research should be done on international defense companies, whose sponsor countries operate under different paradigms in relation to defense than the US.

2. This research focused on defense company acquisitions; further research should expand beyond defense companies to include more general technology companies and identify models that are not specific to the defense industry. Defense models may not apply to non-defense companies, as they operate under different commercialization and financial factors.
3. It is important to expand the machine learning models to deep learning networks or other types of ML techniques beyond the ones outlined in this document. The field of machine learning is constantly expanding and there are more options for ML. New techniques have the potential to provide even more accuracy in forecasting innovation results of M&A.
4. This research focused on one measure of innovation, but there are many different measures of innovation, including external and internal. Expanding the research to use more than one metric of innovation could increase the body of knowledge.

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Appendix A List of Defense Companies Used in Analysis

A1. List of Defense Companies

Table A-1 shows the companies used as inputs to the ML models. The companies were selected based on the criteria outlined in Section 3.2.1.

Table A-1 List of defense companies used for analysis

Aerojet Rocketdyne Holdings	Huntington Ingalls Industries
Airbus	L-3 Communications
Alliant Techsystems	L3 Harris Technologies
BAE Systems	Leonardo DRS
Bell Helicopter	Lockheed Martin
Booz Allen Hamilton	ManTech
BWX Technologies	Mercury Systems
CACI International	Northrop Grumman
Collins Aerospace	Oshkosh
CSC	Precision Castparts
Curtiss-Wright	Raytheon
EDS (Electronic Data Systems)	SAIC
Engility	Sikorsky Aircraft
General Atomics	The Boeing Company
General Dynamics	Triumph Group
Goodrich	United Technologies
Hewlett Packard Enterprise	URS Corporation

Appendix B

B1. Acquisition Dataset Fields

Table B-1 shows the acquisition dataset values, and their ranges used by the ML models.

Table B-1 Acquisition Dataset Fields

Input	Type	Value Range
Acquiree Industry Group	Category	Consumer Electronics Government and Military Hardware Information Technology Manufacturing Privacy and Security Professional Services Science and Engineering Software

Input	Type	Value Range
Acquirer Industry	Category	Aerospace Broadcasting Commercial Cyber Security Data Integration Enterprise Software Industrial Information Technology Manufacturing Mobile National Security Navigation Public Transportation Satellite Communication Security Service Industry Software Transportation Wireless
Acquiree Last Funding Type	Category	Private Equity Series B Series A Debt Financing Series C Series D Undisclosed Venture - Series Unknown Series F Seed Grant Series E Corporate Round Post-IPO Equity Secondary Market
Acquiree's Number of Funding Rounds	Numeric	1-12
Acquiree's Total Funding Amount Currency (in USD)	Numeric	130000 - 279999994

Input	Type	Value Range
Acquirer Funding Status	Category	IPO M&A Seed
Acquirer Name	Category	See Appendix A for list of Companies
Acquirer's Estimated Revenue Range	Category	$1M to $10M $50M to $100M $100M to $500M $10M to $50M $1B to $10B Less than $1M $500M to $1B $10B+
Acquirer's Number of Funding Rounds	Numeric	1 - 6
Acquirer's Total Funding Amount Currency (in USD)	Numeric	3000000 - 1711760000
Acquisition Status	Category	#N/A Was Acquired Made Acquisitions Was Acquired
Acquisition Terms	Category	Stock Cash Cash & Stock
Acquisition Type	Category	Acquisition Merger
Actively Hiring	Category	#N/A Yes
Announced Year	Numeric	1995 - 2017

Input	Type	Value Range
Estimated Revenue Range	Category	Less than $1M $1M to $10M $10M to $50M $50M to $100M $100M to $500M $500M to $1B $1B to $10B $10B+
Founded year	Numeric	1901 - 2018
IPO Status	Category	Delisted Private Public #N/A
IPqwery - Patents Granted	Numeric	Private
IPqwery - Trademarks Registered	Numeric	Public
Last Equity Funding Type	Category	Corporate Round Post-IPO Equity Private Equity Seed Series A Series B Series C Series D Series E Series F Undisclosed Venture - Series Unknown #N/A
Last Funding Amount Currency (in USD)	Numeric	3750 - 220000000
Last Funding Date	Numeric	32874 - 44512

Input	Type	Value Range
Last Funding Type	Category	Corporate Round Debt Financing Grant Post-IPO Equity Private Equity Secondary Market Seed Series A Series B Series C Series D Series E Series F Undisclosed Venture - Series Unknown #N/A
Number of Acquisitions	Numeric	1 - 83
Number of Articles	Numeric	0 - 1392
Number of Employees	Category	1-10 11-50 51-100 101-250 251-500 1001-5000 5001-10000 10001+ #N/A
Number of Exits	Numeric	0 - 1
Number of Exits (IPO)	Numeric	0 - 1
Number of Founders	Numeric	0 - 5
Number of Funding Rounds	Numeric	0 -12
Number of Investments	Numeric	0 -2
Number of Investors	Numeric	1 - 16
Number of Lead Investors	Numeric	1 - 6

Input	Type	Value Range
Number of Portfolio Organizations	Numeric	0 - 2
Operating Status	Category	Active Closed
Price Currency (in USD)	Numeric	2800000 - 30000000000
Total Equity Funding Amount Currency (in USD)	Numeric	130000 - 276000000
Total Funding Amount Currency (in USD)	Numeric	130000 - 279999994