Association of Autoimmune Conditions and Cardiovascular Diseases; Investigated through the analysis of machine learning effectiveness

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Word count: 3,551

Abstract

Autoimmune diseases involve the immune system attacking its own cells because of antibodies that bind to self-antigens, namely at the CDRs (Complementarity-Determining Regions). Having such problems with immune responses also leads to damage to other bodily functions. People with autoimmune diseases, such as Rheumatoid Arthritis (RA), are known to have a particular risk linked to their cardiovascular health. It is due to inflammation, causing vascular damage. Systemic Lupus Erythematosus (SLE) is another autoimmune disease that attacks multiple tissues and organs. Despite being 2 different autoimmune diseases, RA and SLE both have a similar impact concerning issues in the cardiovascular system (Drosos, 2024).

The main pathways linking autoimmune systems to the cardiovascular problems are 2 biological markers: C-Reactive Protein (CRP), an inflammatory marker that binds to damaged cells and triggers responses to measure the extent of effect that inflammation has on the case of heart disease. The other biological marker is Low-Density Lipoprotein (LDL), a protein that carries cholesterol from the liver to cells. Despite having different functions, stats on these measures provide a clear indication of the autoimmune effect. Particularly with a cardiovascular problem, higher measures indicate signs of inflammation (Frostegard, 2002).

Despite the constant advancements in science, researchers haven't been able to dive into the exact association between these variables. Initiatives are being taken, however, especially with

the most recent trend, AI usage. However, the main implementation of AI so far is mainly used for programmed prediction models, which are prone to bias risk potential (Navarro, 2021).

Keywords: Autoimmune conditions, Cardiovascular diseases, Machine Learning

Introduction

Autoimmune diseases generally have their functioning work around the immune system, attacking its own tissues as it sees them as threats. The damage that occurs from such actions, internally and/or externally, is known to be the symptoms of such issues. The relevance that markers like CRP and LDL specifically play in these issues comes into specific risks. When looking at additional problems associated with these conditions, like cardiovascular problems, these markers can identify significant indications.

Although research has been done on individual metrics, there has not been a conclusive study on this cardiovascular topic. This study explores the extent to which machine learning models predict cardiovascular risk in patients with autoimmune disease, using inflammatory markers to compare across diseases like RA and SLE. Since cardiovascular diseases have such a profound effect on various groups, it is important to investigate a connection to this trend in correlation to a more expansive health concern like autoimmune diseases. The technological aspects also have relevance, as the specific terms of AI performance should also be seen for modern implementations.

Methods

Materials

For this investigation, a quantitative study is used. This study primarily looked into certain statistics as the bar measures, and compared data on such scales to get to the answer. To answer the medical part of the question, a case study was analyzed. This is the methodology that was chosen because case studies give in-depth information into particular problems. Cases with patients having the appropriate form of diagnosis can allow studies to dive deep into numbers and come to an answer.

On the technical side, 2 different programs were coded for the second part of the question. In order to measure whether or not machine learning algorithms give a benefit, prediction models were tested through Python codes created on Google Colab. With some syntax coded in different IDEs like VSCode and Replit (for transport of code), both programs were ready to test. This procedure involves 1 program having a machine learning (ML) algorithm and some extra information to showcase its data outputs, while the other program sticks to primarily showing the indication graph itself. The ML program used logistic regression programming to show its results. Logistic Regression is the computational method that's chosen because of its proficiency in creating highly accurate visual models and its ability to be trained to various forms of data (Stolzfus, 2011). The additional codes in that program aim to provide a visual simulation of CRP levels in a patient with a cardiac inflammatory disease in the span of 1 week,

and a boxplot comparison between RA and SLE to find which one has a higher CRP level, to determine which disease has a higher inflammatory effect. For the second model, it is programmed using some stimuli to have the effect of a simulation study, in order to see what the different factors' markers look like. The visuals from the graph are created to give preliminary information on CRP levels throughout a particular timespan, while the boxplots give an idea of which factors' inflammatory effects have a higher likelihood to lead to heart diseases, RA, or SLE, specifically through CRP, which specializes in that index (Sproston, 2018). Neither of these programs is created with raw patient data; rather, they're programmed with simulated patient values to give a more common perspective. Using data sets that use simulated numbers from more cases gives a more generalized view for comparison.

```
import numpy as np
import matplotlib.pyplot as plt

# --- Simulated data ---
days = np.linspace(0, 7, 100)  # 0 to 7 days
# Create a CRP curve: rises, peaks, then declines
crp_levels = 3.2 * np.exp(-0.5 * (days - 3)**2 / 2) + 0.2  # Gaussian-like curve

# --- Plotting ---
plt.figure(figsize=(8,5))
plt.plot(days, crp_levels, color="black", linewidth=2)

# Labels and title
plt.title("Simulated C-Reactive Protein levels following cardiac inflammation onset", fontsize=11)
plt.xlabel("Days since onset", fontsize=10)
plt.ylabel("CRP Levels (mg/L)", fontsize=10)

# Tidy up
plt.grid(False)
plt.show()
```

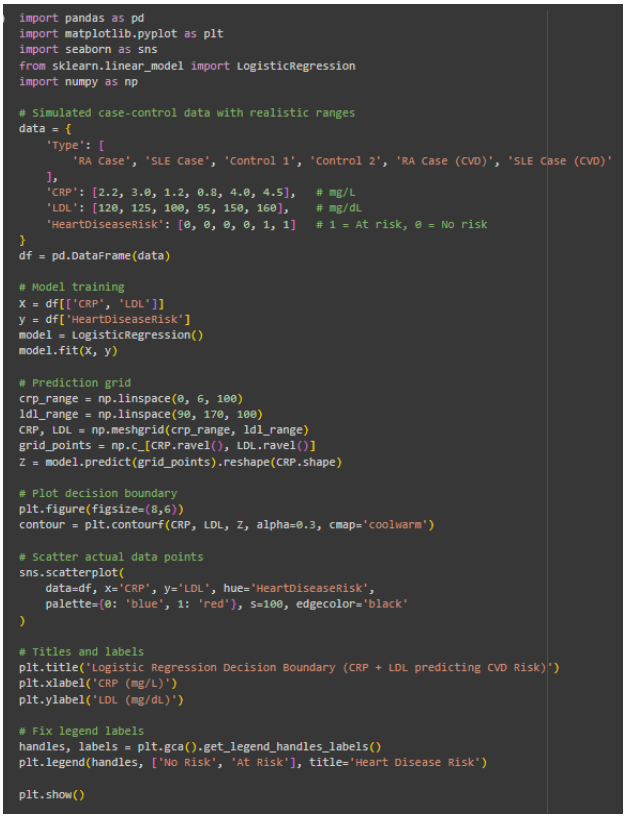
Figure 1| Simulated program for CRP after cardiac inflammation onset.

The code generates a graph that looks into CRP level progression across multiple days.

```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# --- Updated dataset: all RA and SLE cases show heart disease ---
data = {
    'Autoimmune_Type': ['Lupus', 'RA', 'Lupus', 'RA', 'Lupus', 'RA'],
    # CRP values within clinical ranges (<5 mg/L), adjusted for risk
    'CRP_Level': [4.2, 3.8, 3.8, 3.5, 3.5, 3.2],
    'LDL': [135, 145, 150, 138, 142, 139],  # realistic LDL values
    'Heart_Disease': [1, 1, 1, 1, 1, 1]  # now all cases show heart disease
}
df = pd.DataFrame(data)

# --- Visual comparison ---
plt.figure(figsize=(7,5))
sns.boxplot(data=df, x='Heart_Disease', y='CRP_Level', hue='Autoimmune_Type')

plt.title('CRP Levels vs Heart Disease across Autoimmune Types')
plt.xlabel('Heart Disease (1 = Yes, 0 = No)')
plt.ylabel('CRP Level (mg/L)')

plt.show()
```

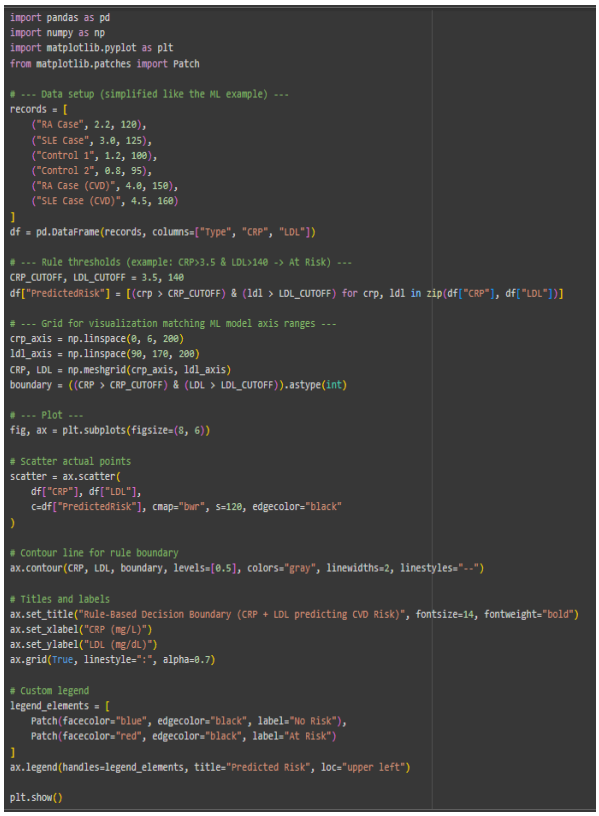
Figure 2| Simulated program for graph that compares CRP and LDL levels to examine severity of cardiovascular impact.

The other program is a control variable that is expected to show a very similar graph to the other code, but it is coded with all the information and not trained like the other model. The main point of comparison will come from the graph that shows the correlation between CRP and LDL statistics. Using both of these variables, both models show simulated patients with certain CRP and LDL levels to determine if they are at cardiovascular risk or not.



```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
import numpy as np

# Simulated case-control data with realistic ranges
data = {
    'Type': [
        'RA Case', 'SLE Case', 'Control 1', 'Control 2', 'RA Case (CVD)', 'SLE Case (CVD)'
    ],
    'CRP': [2.2, 3.0, 1.2, 0.8, 4.0, 4.5],   # mg/L
    'LDL': [120, 125, 100, 95, 150, 160],    # mg/dL
    'HeartDiseaseRisk': [0, 0, 0, 0, 1, 1]   # 1 = At risk, 0 = No risk
}
df = pd.DataFrame(data)

# Model training
X = df[['CRP', 'LDL']]
y = df['HeartDiseaseRisk']
model = LogisticRegression()
model.fit(X, y)

# Prediction grid
crp_range = np.linspace(0, 6, 100)
ldl_range = np.linspace(90, 170, 100)
CRP, LDL = np.meshgrid(crp_range, ldl_range)
grid_points = np.c_[CRP.ravel(), LDL.ravel()]
Z = model.predict(grid_points).reshape(CRP.shape)

# Plot decision boundary
plt.figure(figsize=(8,6))
contour = plt.contourf(CRP, LDL, Z, alpha=0.3, cmap='coolwarm')

# Scatter actual data points
sns.scatterplot(
    data=df, x='CRP', y='LDL', hue='HeartDiseaseRisk',
    palette={0: 'blue', 1: 'red'}, s=100, edgecolor='black'
)

# Titles and labels
plt.title('Logistic Regression Decision Boundary (CRP + LDL predicting CVD Risk)')
plt.xlabel('CRP (mg/L)')
plt.ylabel('LDL (mg/dL)')

# Fix legend labels
handles, labels = plt.gca().get_legend_handles_labels()
plt.legend(handles, ['No Risk', 'At Risk'], title='Heart Disease Risk')

plt.show()
```

Figure 3| Logistic Regression Prediction Model code that uses machine learning to examine cardiovascular impact through inflammatory markers.



```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.patches import Patch

# --- Data setup (simplified like the ML example) ---
records = [
    ("RA Case", 2.2, 120),
    ("SLE Case", 3.0, 125),
    ("Control 1", 1.2, 100),
    ("Control 2", 0.8, 95),
    ("RA Case (CVD)", 4.0, 150),
    ("SLE Case (CVD)", 4.5, 160)
]
df = pd.DataFrame(records, columns=["Type", "CRP", "LDL"])

# --- Rule thresholds (example: CRP>3.5 & LDL>140 -> At Risk) ---
CRP_CUTOFF, LDL_CUTOFF = 3.5, 140
df["PredictedRisk"] = [(crp > CRP_CUTOFF) & (ldl > LDL_CUTOFF) for crp, ldl in zip(df["CRP"], df["LDL"])]

# --- Grid for visualization matching ML model axis ranges ---
crp_axis = np.linspace(0, 6, 200)
ldl_axis = np.linspace(90, 170, 200)
CRP, LDL = np.meshgrid(crp_axis, ldl_axis)
boundary = ((CRP > CRP_CUTOFF) & (LDL > LDL_CUTOFF)).astype(int)

# --- Plot ---
fig, ax = plt.subplots(figsize=(8, 6))

# Scatter actual points
scatter = ax.scatter(
    df["CRP"], df["LDL"],
    c=df["PredictedRisk"], cmap="bwr", s=120, edgecolor="black"
)

# Contour line for rule boundary
ax.contour(CRP, LDL, boundary, levels=[0.5], colors="gray", linewidths=2, linestyles="--")

# Titles and labels
ax.set_title("Rule-Based Decision Boundary (CRP + LDL predicting CVD Risk)", fontsize=14, fontweight="bold")
ax.set_xlabel("CRP (mg/L)")
ax.set_ylabel("LDL (mg/dL)")
ax.grid(True, linestyle=":", alpha=0.7)

# Custom legend
legend_elements = [
    Patch(facecolor="blue", edgecolor="black", label="No Risk"),
    Patch(facecolor="red", edgecolor="black", label="At Risk")
]
ax.legend(handles=legend_elements, title="Predicted Risk", loc="upper left")

plt.show()
```

Figure 4| Standard Prediction Model that uses hard coded variables to analyze inflammatory markers' effects on cardiovascular diseases.

When looking at the medical aspect of the question (autoimmune effect on heart diseases), a different methodology was used. This part of the study used a qualitative analysis, as the proposed answer is expected to be explained in a written manner that is better shown in a thoroughly demonstrable explanation. Because of this planned methodology, a case study analysis was used as the source that can give key details on the biological impact of the patient's

situation. Looking through a case study thoroughly, while knowing which statistics to look for, helped the researcher get into the specifics of the autoimmune impact. The case study that was used was selected through a process that looks for specific terminology.

The patient must have Rheumatoid Arthritis and Lupus Erythematosus to bring in the autoimmune perspective, with the specific stats that are needed. Even a mixed condition like Rhupus, a symmetrical overlapping of both cases, could be used for analysis due to its mixed nature (Upadhyaya, 2022). Along with that, they must have some form of cardiovascular risk, such as strokes or infarctions, for the clear indicators of risk. This must be present in order for the question to get tied back into how issues with one's immunology create problems for the heart's health. After the case study was found, the programs and the study were ready to be analyzed.

Data Collection

In order to get a reference on statistical data to expect from RA and SLE, a box plot was programmed with significant measures. Particularly, CRP is the measure that is supposed to be used (as an autoimmune marker) to show the correlating chances of heart disease. This model essentially simulated at what CRP levels for each of these autoimmune conditions, heart disease would likely take a toll on. Using that base information, some individual analysis was conducted with the case study itself, and looked into specific measures as well.

From the procedure mentioned to find the case study, a particular case study was found on a 43-year-old woman who is a rhupus patient having coronary aneurysms and myocardial infarction. With the thorough overview of this document, important hypotheses were documented, such as how certain conditions of hers affect other bodily functions, and how they lead to problems like cardiovascular risks. After the case study analysis, the computer programs were put to use as they were given crucial stimuli to start with. The outputs that were generated and recorded were used to find patterns and trends that would be useful.

Analysis

This data enabled further generalizations as the study went back to collect some unidentified data from the case study. Using the initial analysis of this case study, which noted cardiovascular problems like aneurysms and infarctions, diseases like atherosclerosis were also hinted at. Such points from this case study were used to individually investigate them to get an approximation of this patient's CRP and LDL levels. With this newfound data, it was then analyzed according to the visuals produced by the first 2 codes in the ML program to clarify if all measures were accurate. This step in particular looked into predicting how the woman's CRP levels would have looked after the onset of any heart problems, with her estimated CRP numbers. That model also helped verify that her CDR levels indeed would have taken a peak after 2-3 days after the onset to show the most amount of impact. With the boxplot model, her

conditions of RA and Lupus were interpreted in a way that compares her estimated CRP values to how much each of her autoimmune diseases had an impact on her heart health.

Evaluation

Using the preliminary analysis of this case study, combined with the computational outputs, certain interpretations were made. The specific conditions and problems with the woman were factored along with the new understanding of the analyzed factors, which led to the answer from the medical perspective of the research question, which investigated biological factors associated with autoimmune diseases that cause inflammatory cardiovascular problems.

With all this context ready, both of the main prediction codes from each program were tested. The outputs from both models were compared to see what the main differences were that the ML program had that the control didn't. Along with that, the codes were also analyzed through their syntax to see differences. Finally, the conclusion from the case study analysis and the comparison of the computational outputs were shown synchronously to answer both parts of this study.

Results

Case study findings

What can be seen from the case study of the 43-year-old woman with Rhupus is that she has a pre-history of autoimmune diseases. The main cardiovascular problems noted in her case are coronary aneurysms and a myocardial infarction. These issues further indicate potential vascular

damage and serve as a strong sign of cardiac ischemia. Inflammation didn't play a dominant role; it's most likely that the overlap condition (Rhupus) contributed to the vascular damage. Other diseases, like atherosclerosis, in combination with the autoimmune-based vascular effects, are what cause the cardiovascular problems.

Indication programs

After analyzing the case study and the notes taken from it, they were studied along with the computational outputs. When looking at the output for the boxplot comparison, it shows that SLE has a range of higher numbers and a better average of CRP levels in comparison to RA. The median value shows Lupus having a CPR level of 3.8 mg/L, while RA had a level of 3.5 mg/L. SLE's impact is further seen as its CRP level range for cardiovascular impact is 3.5-4.2 in comparison to RA's range of 3.2 to 3.8. This finding essentially points out that due to higher CRP levels, SLE has a higher inflammatory effect on cardiovascular diseases in comparison to RA.

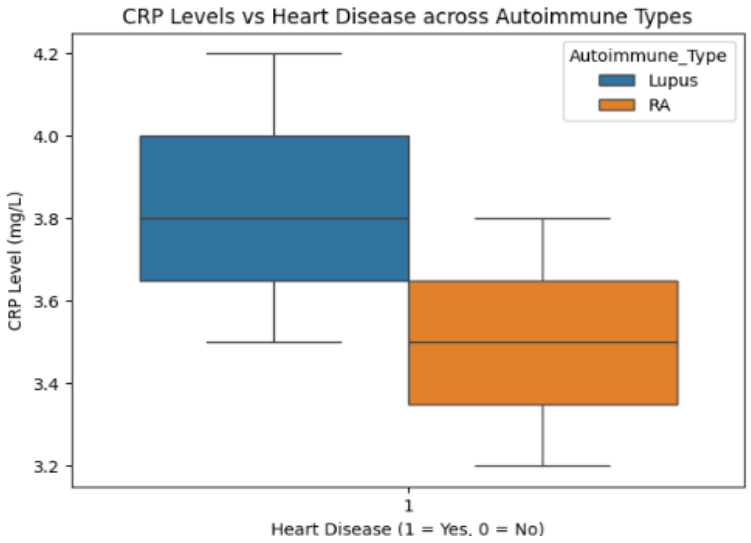


Figure 5| Boxplot comparison model

The secondary model in that program, which had the dataset file with numbers for CRP levels after cardiac onset, projected a downward parabola. Using some prediction of graph points, used by the initial analysis of this case study, the program showcased the results in a way that expresses an initial growth in CRP levels, hitting a peak at 3-4 days, and eventually falling back to lower levels in the remainder of the week.

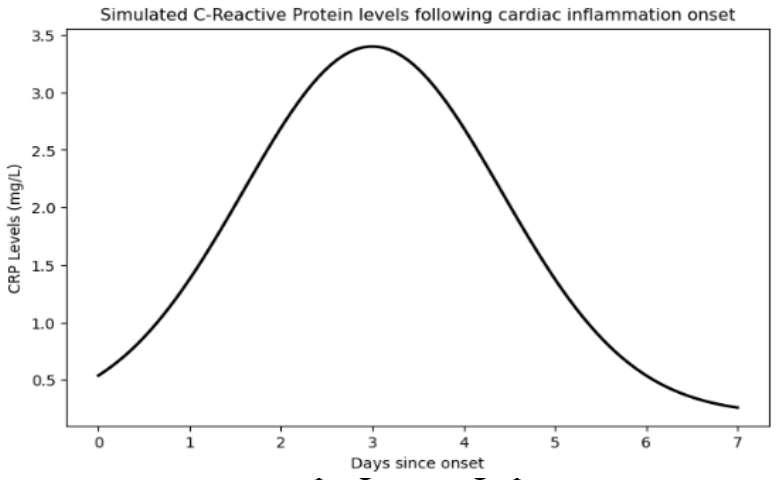


Figure 6| CRP progression graph

Prediction Models

The CVD risk prediction model with logistic regression and the model with no machine learning (ML) were run to see outputs on both ends. Although they visually look quite similar in terms of predicting risks, the ML model looked more variable with its outputs. It went to the extent of creating regions to showcase at which possible levels of CRP and LDL, risk would intensify. On the other hand, the control variable's code was, at best, able to narrow out the region where the simulated CRP/LDL levels would fall under CVD risk.

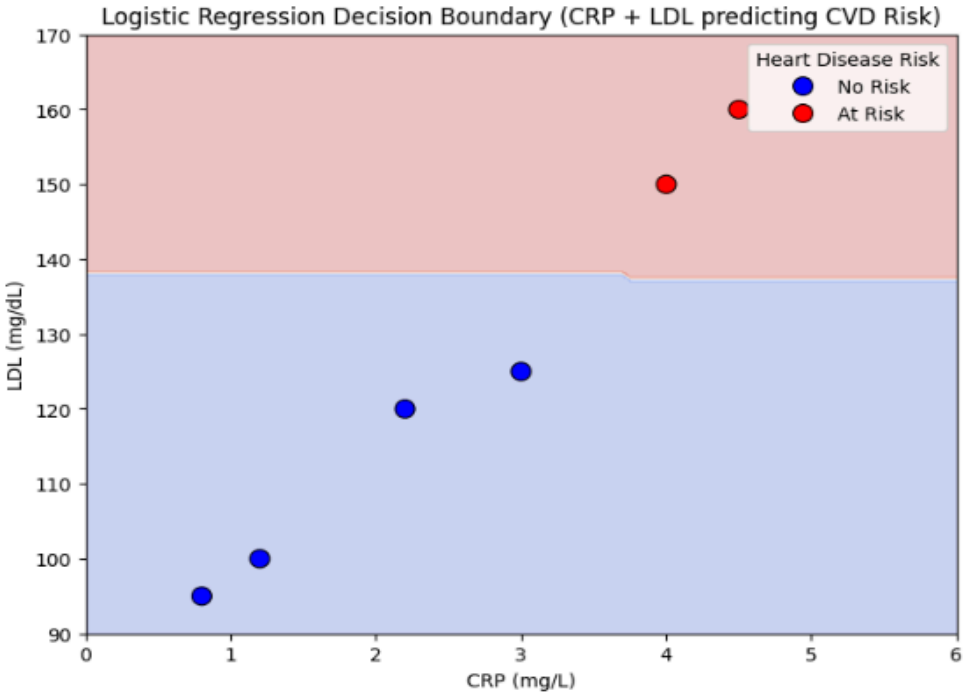


Figure 7| Logistic regression model output

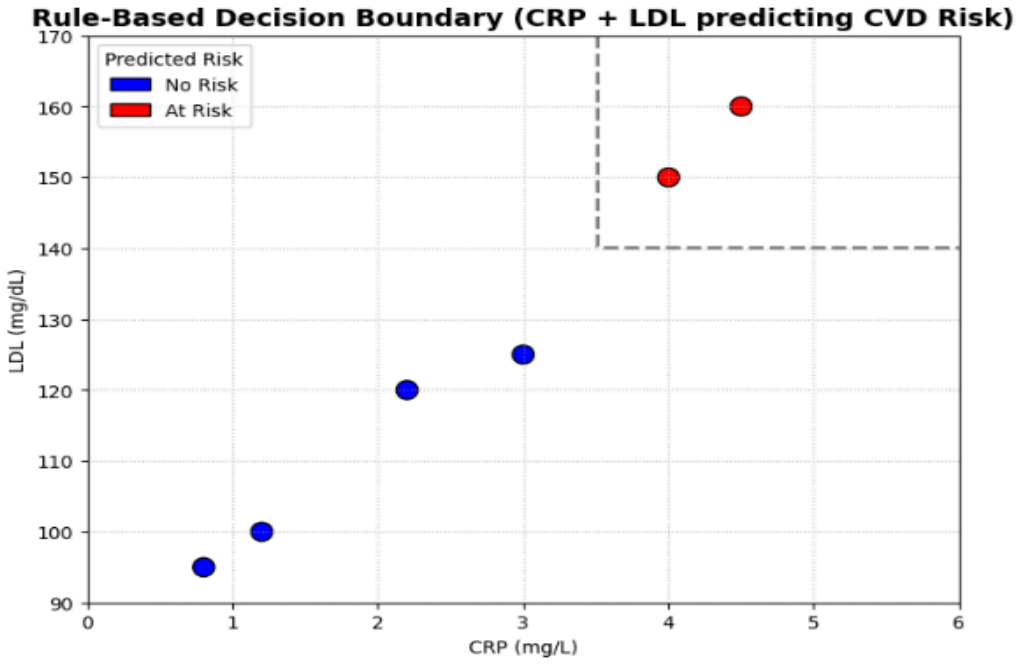


Figure 8| Control model output

Discussion

Initial programs

Using the findings from the first 2 programs, a lot of stimulus-related context was seen. Seeing that Lupus has a higher median and better range in CRP levels signals a larger risk of inflammatory cardiovascular problems. In this comparison between RA and SLE, Lupus seems to be more likely seen in a more aggressive inflammatory environment, which poses a larger degree of risk to vascular injuries. Although both autoimmune diseases have increased inflammatory problems, SLE's more versatile impact through various aspects keeps it at a higher risk, as seen by the higher CRP levels. Since Lupus is also a systemic disease, it is more likely to affect the human body further than a disease like RA (Wu, 2025).

The simulated progression of CRP levels after onset reflects that there is a gradual increase and hits a peak, after which it begins to decline. This curve serves as a prognostic biomarker to measure the inflammatory impact. This reflects that the inflammatory effect on cardiovascular health doesn't just stay dormant but also has different progressions. Because of this time-sensitive aspect, it is also used to assess on which day the most impact can be noticed. Using this finding, the day/s with the highest CRP levels (3-4) could be analyzed in particular to see the most inflammatory effects on one's cardiovascular health. Although CRP levels can't single-handedly predict cardiovascular inflammatory problems, there is a strong correlation

factor between these variables, which signals caution in multiple areas, from infections to vascular damage, pertaining to heart health (Liu, 2024).

Key analysis :

The comparison between the machine learning program and the control model is used to show the particular strengths in the usage of trained models for such cases. Seeing the control model's fixed nature and more static output, it seems quite difficult to reflect multiple variables. The pre-defined ranges highlight this program's rigidity, which would make it more difficult to show nuanced shifts in the patient's likelihood of cardiovascular risk if CRP/LDL levels changed, as shown from the CRP progression graph. The logistic regression model, on the other hand, gave a wider range of outputs with marked regions to clearly show at what intervals or CRP/LDL levels one falls under inflammatory cardiovascular risk. It also highlights a larger difference between CRP and LDL as it captures subtle interactions between the various biomarkers.

In terms of effectiveness, the logistic regression model also seems superior due to its more detailed visualizations. In any form of scientific analysis, outputs with more clarity provide better potential for research. In that way, the output from the ML model includes more elements by dynamically incorporating CRP and LDL levels into identifying regions under which certain ranges fall under cardiovascular risk. Although the control variable also has that feature, it is more limited in that it has fixed regions for cardiovascular risks. Instead of being able to shift to analysis of different CRP/LDL statistics, the control is only able to keep a certain region, and

beyond that, in the risk zone, and only simulated values in that threshold get classified as being in risk. Due to this difference, the ML model is able to predict more cases of cardiovascular risk in comparison to the control code, which only uses standardized requirements to predict chances of risk.

From a programming perspective, the ML model required training to give visualizations in an expected way that can adapt in different forms. The input data was then projected with smooth results using the logistic regression programming to give the possibility of easily using multiple datasets. On the other hand, since the control variable used hardcoded syntax, all the values had to be predefined using pre-analytic procedures. Because of these additional procedures, key analysis gets stalled as this model cannot be adapted or taught, unless variables are hard-coded into the program.

When these outputs are centered around the case study analysis, a complete result emerges with all the variables rounded up. The patient did have cardiovascular problems like coronary aneurysms and myocardial infarction, but when noticed, said that inflammatory levels weren't too impactful in these issues. This suggests that at the point of testing, the patient may have had lower CRP levels, hence showing less inflammation. When looking at this point side by side with the CRP progression model, it suggests that the patient might have been tested on a day when the CRP curve was on a decline (days 5-7).

Perhaps, on a day where the CRP levels are high (like days 3-4), different results could potentially be noted. When looking deep into the timely significance of this biomarker activity, an external perspective like Rhupus is involved. Rhupus is an overlap autoimmune disease itself, and its side effects trigger stress-based cardiovascular diseases. As noted before, the patient's vascular damage was caused by her atherosclerosis, and Rhupus could be a significant factor in influencing that. Not just this overlap, but people with RA and SLE conditions, respectively, could encounter issues pertaining to chronic inflammation and related mechanisms, which drive an accelerated atherosclerosis (Full, 2009).

Conclusion

This study demonstrates that systemic lupus erythematosus poses a greater inflammatory cardiovascular risk than rheumatoid arthritis, with higher C-reactive protein levels and stronger associations with multiple body systems, particularly vascular impact. The CRP levels also showcase the significance of timely analysis, as different points of testing showcase different inflammatory results, which at their peak levels could be influenced along with autoimmune effects from diseases like Rhupus to trigger atherosclerosis. The cardiovascular risk is hence defined through issues like myocardial infarctions, coronary aneurysms, strokes, etc., which are caused by problems like rhupus-driven atherosclerosis. The machine learning models have a large impact on the prediction of cardiovascular risk from an efficiency and accuracy standpoint. The ML program, particularly using logistic regression, has an adaptable nature to

its programming, where it can be trained for a variety of case analyses, along with properly utilizing biomarkers like CRP and LDL to mark risks. This model is also highly accurate in comparison to standard models, as its software complexity enables it to project even nonlinear relationships between the biomarkers and accurately predict more cases.

Put together, SLE has a higher inflammatory impact on cardiac cases, with CRP showing autoimmune disease effects to exacerbate cardiovascular risk through its multifaceted impact, which is strongly predicted by ML models due to its efficient and accurate predictions.

Limitations

Although the study utilized multiple variables and had a thorough analysis, some limitations do exist. These computational programs utilized disease datasets instead of implementing raw patient data, which could've further emphasized generalizability. Along with that, more complex biomarkers such as IL-6 and ESR could've been used to further showcase inflammatory effects. Only CRP and LDL were used in particular to have a more narrow approach, which in turn reduces the generalizability. There are more areas of potential expansion: More ML models being tested beyond logistic regression, and having more than just 1 case study. These requirements were only analyzed in such a way to keep the structure more understandable and to prevent a lack of focus in the study, with an excessive amount of variables being factored in.

Significance and Implications

Since this study looks into medical and technical perspectives, future research on this topic can benefit multiple fields. Since cardiovascular problems like MI and atherosclerosis are highly common among the general population, research into the autoimmune connection also looks into further aspects of such diseases. The technical analysis of this research involving the computational programs also shows how artificial intelligence could be programmed to assist further biological research. The clinical aspect of this study also holds significance as there's a large population with autoimmune diseases like RA & SLE, which could be studied to look into further exacerbating factors. In terms of demographics, this research would particularly apply to those of above 50 years old. Since cardiovascular diseases are more common among the elderly aged, the technological assistance could have better implications when addressing people of these age groups. Specifically, highly developed countries could implement such research. Countries like America have a large elder population with a large risk of CVDs. When factoring in America's technological developments, such forms of research is ideal in treating further problems. Future research can specifically focus on using more datasets, along with a larger number of case studies directly incorporated into advanced ML programs to gain further insight into the usage of AI in this form of multidisciplinary scientific research.

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