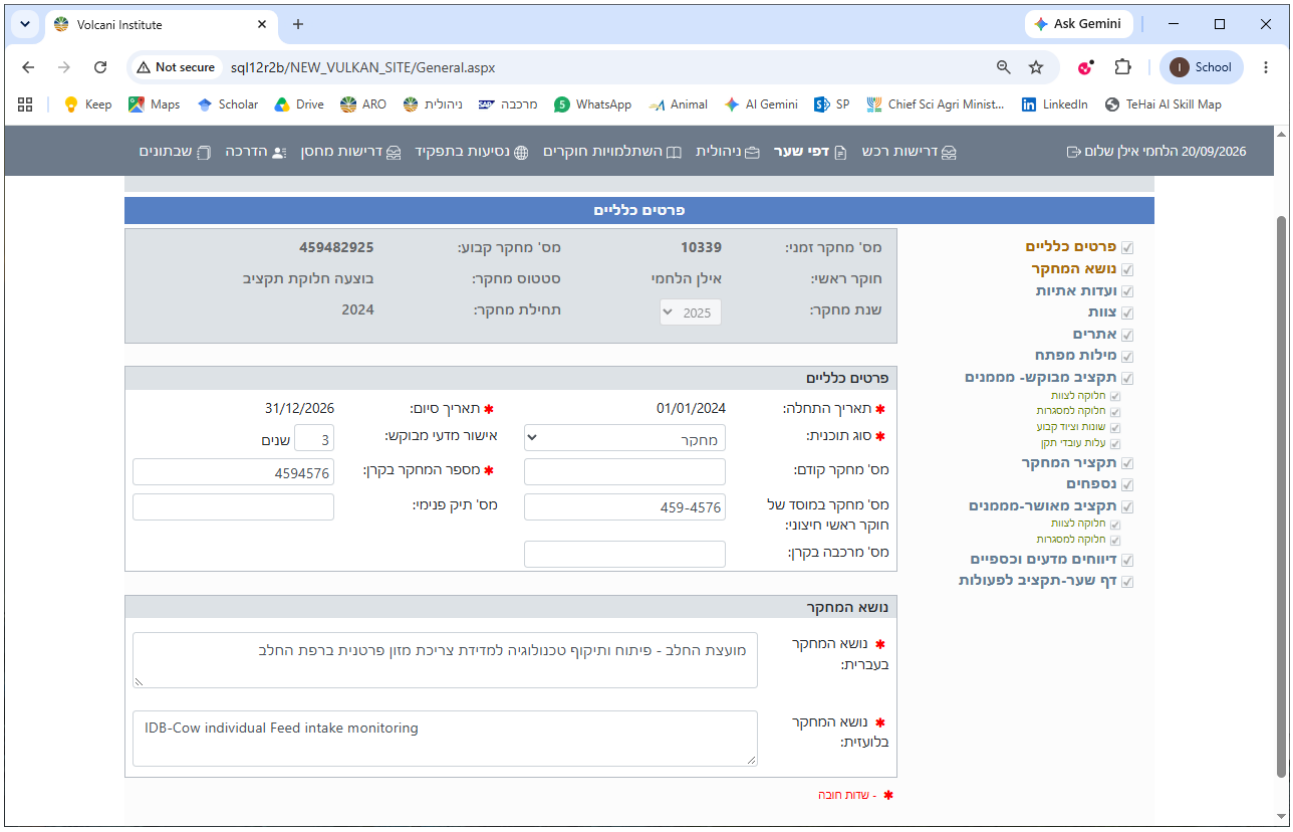
דף השער הרשמי של מכון וולקני. שנה שנייה מתוך שלוש.



חיים/שמוליק, ראיתי בהוראות שצריך להתחיל בדף שער רשמי של קרן המחקרים של מועצת החלב. אין לי גישה אליו. אשמח אם תצרף.

דוח מדעי - שנה שנייה

מועצת החלב - פיתוח ותיקוף טכנולוגיה למדידת צריכת מזון פרטנית ברפת החלב

שנה II. מערכת למדידה נפחית של צריכת מזון פרטנית ברפת מסחרית

מוגש לקרן המחקרים של מועצת החלב

20 בספטמבר 2026 עדכון של מצגת שהוצגה בוועדה באוגוסט 2025.

מוסד מבצע: מכון וולקני - המכון להנדסה חקלאית, המעבדה לחקלאות מדייקת בחיות משק

חוקר ראשי: פרופ' אילן הלחמי

המחקר מבוסס על עבודות קודמות של תלמידי מחקר, בני כץ, אילנה ריכטר, יהושע בן מאיר, רן בזן, מאי סער, נועם ברגמן, רן שמולביץ, אסף פוקס, רובם בהנחייה משותפת עם פרופ יעל אידן, פרופ' אילן שמשוני וד"ר שוקי מירון

תפקיד במחקר	שם
חוקר ראשי - ריכוז המחקר, מתודולוגיה ומימון	פרופ' אילן הלחמי
שותפה מחקרית - ראייה ממוחשבת ולמידת מכונה	פרופ' יעל עדן
הנחייה משותפת של דוקטורנט וגיבוי תזונת מעלה גרה לארך כל השנים	דר' שוקי מירון
פיתוח מודלים, ניתוח נתונים וכתיבת המאמר המדעי	בני כץ (MSc)
פיתוח מערכת חומרה ותוכנה בגרסה אחרונה	רן שמולביץ (MSc)
פיתוח מודלים קודמים למדידת צריכת מזון	רן בזן, מאי סער (MSc)
זיהוי ביומטרי של פרות	נועם ברגמן (MSc)
פיתוח מודלים מוקדמים יותר	אילנה ריכטר, יהושע בן מאיר, אסף פוקס

הערה: זהו דוח סיכום לשנת המחקר השנייה, המהווה גם את שנת הפעילות האחרונה של המחקר במסגרתו הנוכחית במכון וולקני, כמפורט בפרק הסיכום.

תוכן העניינים

1. מבוא ורקע מדעי

2. מטרות המחקר

3. סיכום עמידה ביעדי שנה ב'

4. תיאור המערכת שפותחה

5. עקרון הפעולה ואימות המדידה

6. תוצאות שנה ב'

7. מסקנות

8. סיכום הפרויקט וסיום הפעילות במכון וולקני

9. המלצות להמשך המחקר

10. הפצה מדעית ותודות

נספח ב' - מאמר מדעי מלא (מצורף)

תקציר

מעבדת חקלאות מדייקת של חיות משק (PLF) מציבה את מדידת צריכת המזון הפרטנית כאתגר מרכזי ברפת החלב המודרנית, שכן להזנה נודעת ההשפעה כלכלית גדולה ביותר על רווחיות המשק. שיטות המדידה הקיימות - מודלים מתמטיים, אבוסים מבוססי load cells וחיישנים לבישים - סובלות מדיוק נמוך, תחזוקה או עלות גבוהה לכן ואינן מתאימות ליישום נרחב בתנאי שטח מסחריים.

במסגרת המחקר בשנה II פותחה ואומתה מערכת חדשנית לא-לבישה למדידה נפחית של צריכת מזון, המבוססת על מצלמות תלת-ממדיות המותקנות מעל פס האבסה וקוראות מפות עומק לפני ואחרי כל אירוע אכילה. בשנת המחקר השנייה הותקנה המערכת ברפת מסחרית בכיסוי של 18 עמדות אכילה, ופעלה ברציפות 24/7 ללא תקלות.

ניסויי אימות הראו כי דיוק המדידה הנפחית עומד על שגיאה קטנה מ-0.6 ליטר ב-95% מהמדידות, ללא תלות בכמות המזון. בנוסף פותחו מודלים מבוססי למידת מכונה: אלגוריתם YOLOv8 לזיהוי פרות בעמדה הגיע לדיוק של 0.95, ומודל Gradient Boosting לחיזוי משקל הארוחה הבודדת הגיע ל-MAE של 1.54 ק"ג (R^2=0.88), על בסיס נתוני 56 פרות ו-365 ארוחות.

שנה זו היא גם שנת הפעילות האחרונה של המחקר במסגרתו הנוכחית במכון וולקני, עקב עזיבת החוקר הראשי את המכון. הדוח מציג המלצות להמשך המחקר על ידי גורם ממשיך - אקדמי, ענפי או מסחרי - לרבות זיהוי ביומטרי, מודל המרה לחומר יבש, ומערכת תומכת החלטה, תוך שהמערכת, הקוד והנתונים יעמדו לרשות כל גורם כזה.

1. מבוא ורקע מדעי

חקלאות מדייקת של חיות משק (Precision Livestock Farming - PLF) היא גישה ניהולית מודרנית המשתמשת בטכנולוגיות מתקדמות לניטור רציף ואוטומטי של בעלי חיים באופן פרטני. מטרת ה-PLF היא לשפר את היעילות התפעולית, רווחת בעלי החיים ורווחיות המשק. אחד האתגרים המרכזיים ל-PLF ברפת החלב המודרנית הוא המעקב אחר צריכת המזון של כל פרה ופרה. הזנה מהווה את ההוצאה הגדולה ביותר ברפת, ומידע מדויק על צריכת מזון פרטנית חיוני למספר מטרות:

- **שיפור ניצולת המזון:** אופטימיזציה של הרכב המנה וכמות נצרכת יכולה להוביל לחיסכון של עד 5% בעלויות ההזנה.
- **ניהול עדר מתקדם:** זיהוי פרות יעילות יותר (מבחינת המרת מזון לחלב) מאפשר קבלת החלטות מושכלת לגבי השבחה גנטית והוצאת פרות פחות כלכליות מהעדר.
- **גילוי מוקדם של בעיות בריאותיות:** ירידה בצריכת המזון היא לעיתים קרובות סימן ראשון למחלה. זיהוי מוקדם מאפשר טיפול מהיר ויעיל יותר, ובכך מקטין את הנזק הכלכלי והפגיעה ברווחת הפרה.

מערכות עדכניות למדידת מזון פרטנית לפרות נחלקות לארבע תפיסות עיקריות: (1) מודלים מתמטיים-פיזיולוגיים, כדוגמת מודל ה-NRC או מודל Halachmi et al. (2004) (2); מדידה ישירה בעזרת אבוסים פרטניים עתירי מכניקה (load cells הממוקמים בתחתית המתקן); (3) חיישנים לבישים המדמים את צריכת המזון על בסיס ניטור פעילות; (4) חישה מרחוק המבוססת על עיבוד תמונה.

מודלים מתמטיים ללא כיול פרטני מקומי מחזירים ערך ממוצע - נכון ברמת העדר אך לא מדויק מספיק להחלטות על הפרה הבודדת. מערכות מבוססות חיישנים לבישים אומצו במספר רפתות מסחריות, אך הציגו רמת דיוק נמוכה מכיוון שהן מבוססות על מודל כללי ולא על מדידה ישירה. מערכות מכניות מבוססות load cell נמצאות בשימוש בעיקר במכוני מחקר, בשל עלותן הגבוהה (כ-6,000 אירו לעמדת האכלה), הצורך בהתקנת תשתית מסיבית ושינוי שגרת העבודה ברפת, ותחזוקה תדירה. מערכות מבוססות עיבוד תמונה, הנשענות על טכנולוגיות חישוב מתקדמות, טרם הבשילו לכדי אמצעי מדידה מדויק המאפשר את הגמישות וכושר ההסתגלות הנדרשים לאימוץ נרחב ברפתות מסחריות, שכן האלגוריתמים שבבסיסן מבוססי-נתונים ודורשים שלבי אימון-בדיקה (train-test) נרחבים עבור כל התקנה ו/או הרכב מזון.

לכן, המחקר הנוכחי עוסק בפיתוח מערכת חדשנית ולא-פולשנית, המבצעת מדידה ישירה (ולא עקיפה בעזרת חיישני התנהגות) של צריכת מזון פרטנית, ופועלת בתנאי רפת מסחרית ללא הפרעה לפעילות השוטפת.

2. מטרות המחקר

פיתוח, יישום ואימות של מערכת מבוססת חישה מרחוק (מצלמות תלת-ממדיות) למדידה אוטומטית, רציפה ומדויקת של צריכת המזון הפרטנית של פרות חולבות בתנאי רפת מסחרית, ללא צורך בתשתית מכנית יקרה ופולשנית וללא הפרעה לשגרת העבודה ברפת.

3. סיכום עמידה ביעדי שנה ב'

- **1. אב-טיפוס:** בוצע תכנון והקמה של מערכת חומרה ותוכנה למדידה נפחית של מזון בפס האבסה.
- **2. התקנה בשטח:** הותקנה מערכת ברפת מסחרית, בכיסוי של 18 עמדות אכילה וכיול ראשוני של המצלמות.
- **3. ולידציה (validation) ראשונית:** בוצעו ניסויי אימות לדיוק המדידה הנפחית של המערכת בתנאי מעבדה ובתנאים מבוקרים ברפת.

שלושת היעדים שהוגדרו לשנה ב' הושגו במלואם, כמפורט בהמשך הדוח.

4. תיאור המערכת שפותחה

בשנת המחקר השנייה פותחה והותקנה מערכת למדידה נפחית של צריכת מזון, הכוללת רכיבי חומרה ותוכנה ייעודיים.

כללי:
המערכת מיועדת למדוד את נפח המזון אשר נצרך בכל עמדה, בכל אירוע אכילה, בתנאי העבודה ברפת מסחרית, ללא הפרעה לשגרת תפעול הרפת.

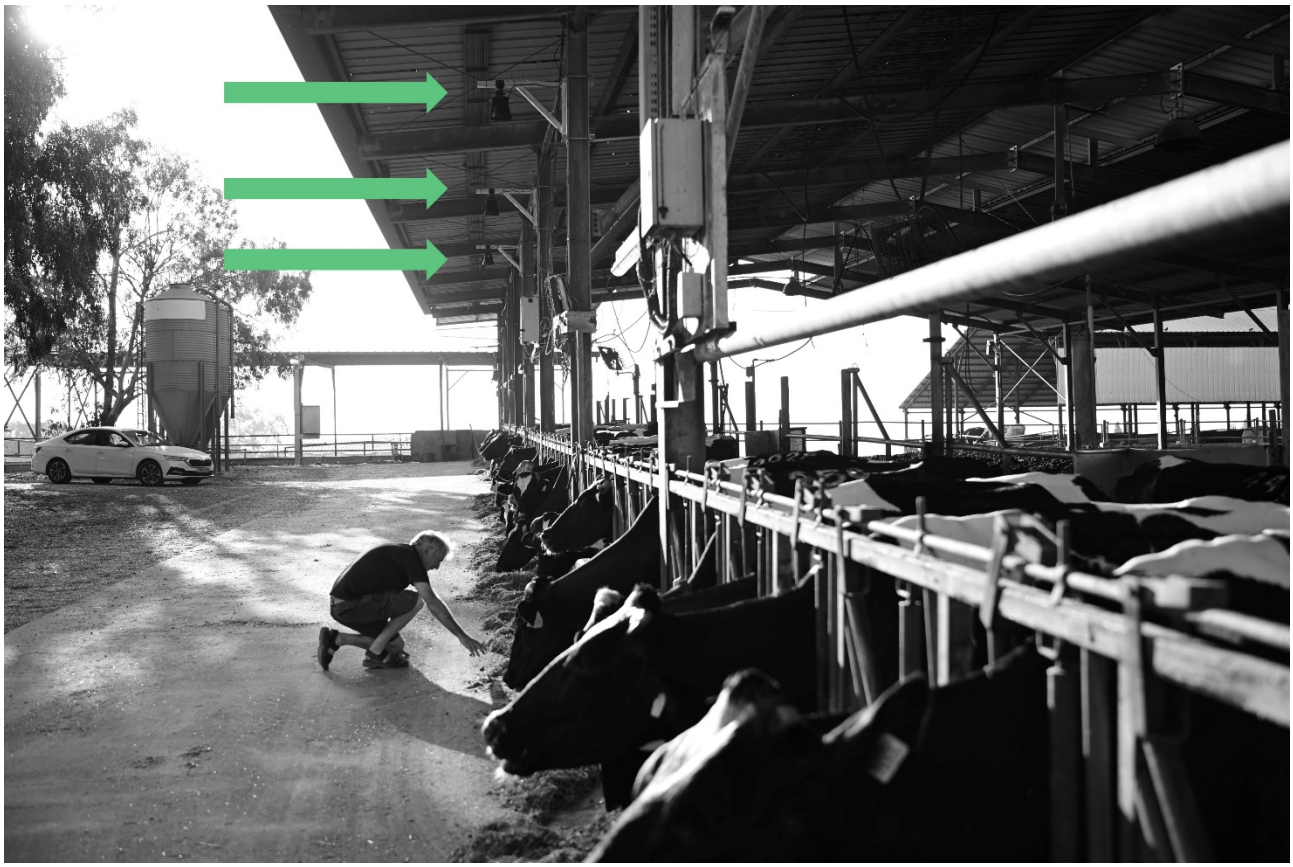
חומרה:

חיישן (להלן יקרא "מצלמה") למיפוי תלת ממדי הותקן מעל פס המזון כך שאינו מפריעה לתפעול. כל מצלמה מכסה כ-6 עמדות אכילה. מתג ETHERNET PoE+ מאפשר ניהול מספר מצלמות במקביל. התוכנה של המצלמות רצה ברפת על מחשב שדה קשיח אשר מתקשר מול המצלמות ומבצע עיבודים בזמן אמת. נתונים אחרי עיבוד - עולים לענן להמשך קבלת החלטות אסטרטגיות. נתב סלולרי מאפשר שליטה ושידור הנתונים מאתר ההתקנה אל רשת האינטרנט. דיסק נייד 2TB מאפשר אחסון הנתונים לטובת תחקור off-line.

מחוץ להישג ידן של הפרות וללא הפרעה לתנועת הטרקטור, המערבל או המשאית המפזרת את המזון. כל מצלמה מכסה 6 עמדות אכילה, ובמערך הנוכחי הותקנו שלוש מצלמות המכסות 18 עמדות. עיבוד הנתונים מתבצע בזמן אמת על גבי מחשב שדה ייעודי, ונתב סלולרי מאפשר שליטה מרחוק ושידור נתונים לענן.

תוכנה:

התוכנה פועלת בשני מצבים עיקריים: מדידת נפח וזיהוי אירוע אכילה. כל עוד עמדת האכילה פנויה, המערכת מודדת את נפח המזון הקיים בה. כאשר מזוהה פרה שנכנסת לעמדה, המערכת מתעדת את הנפח ההתחלתי ואת שעת תחילת האירוע. עם עזיבת הפרה, המערכת מודדת את הנפח הנותר ומחשבת את הנפח שנצרך, משך הארוחה ושעת הסיום. נתונים אלו נשמרים בקובץ ייעודי לצורך ניתוח מאוחר יותר.



איור 1. המערכת מותקנת בתנאים מסחריים. כל חץ מצביע על מצלמה.

4.1 מתכונת הניסוי ברפת

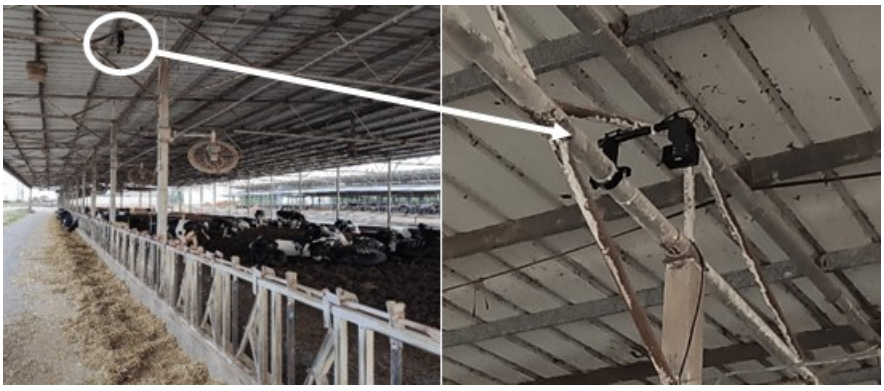
הניסויים לפיתוח ואימות המערכת בוצעו ברפת מכון וולקני, בעדר של פרות חולבות מזן הולשטיין. באזור המצולם הוצבו שני משטחי שקילה אלקטרו-מכניים (load cells בעלי דיוק של 0.023%), האחד מחוץ לטווח הגעתן של הפרות - לצורך מדידת שינויי צפיפות של מזון שאינו נאכל, והשני בטווח הגעתן - לצורך קבלת "אמת מידה" (ground truth) לכימות צריכת המזון בפועל. נתוני החישה מהמצלמות נאספו במקביל לנתוני משקל ממשטחי השקילה, לנתוני הרכב המנה (TMR) ולנתונים סביבתיים (טמפרטורה, לחות, רוח ולחץ ברומטרי), לצורך אימון ואימות המודלים החישוביים המתוארים בסעיף 6.1.

5. עקרון הפעולה ואימות המדידה

עקרון המדידה מבוסס על יצירת מפת עומק (depth map) של המזון באבוס, לפני ואחרי אירוע האכילה. ההפרש בין שתי מפות העומק מאפשר לחשב את נפח המזון שנצרך באמצעות אינטגרציה על הפרשי הגובה.



איור 2. המצלמות מסוגלות לקלוט את המזון ברזולוציה טובה גם מגובה שרכב ברפת עובר מתחתיו ללא הפרעה (המצלמות מודגשות למעלה בתמונה).

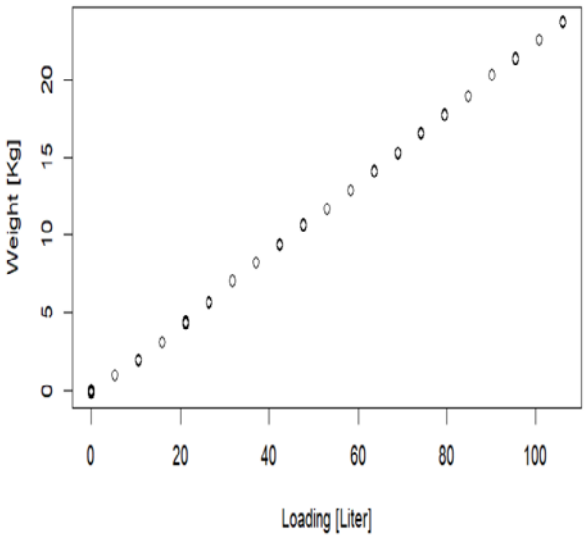


איור 3. התקנת המצלמות במיקום שאינו מפריע לשגרת הרפת (תמונה מהרפת הקודמת, משנה א').

6. תוצאות שנה ב'

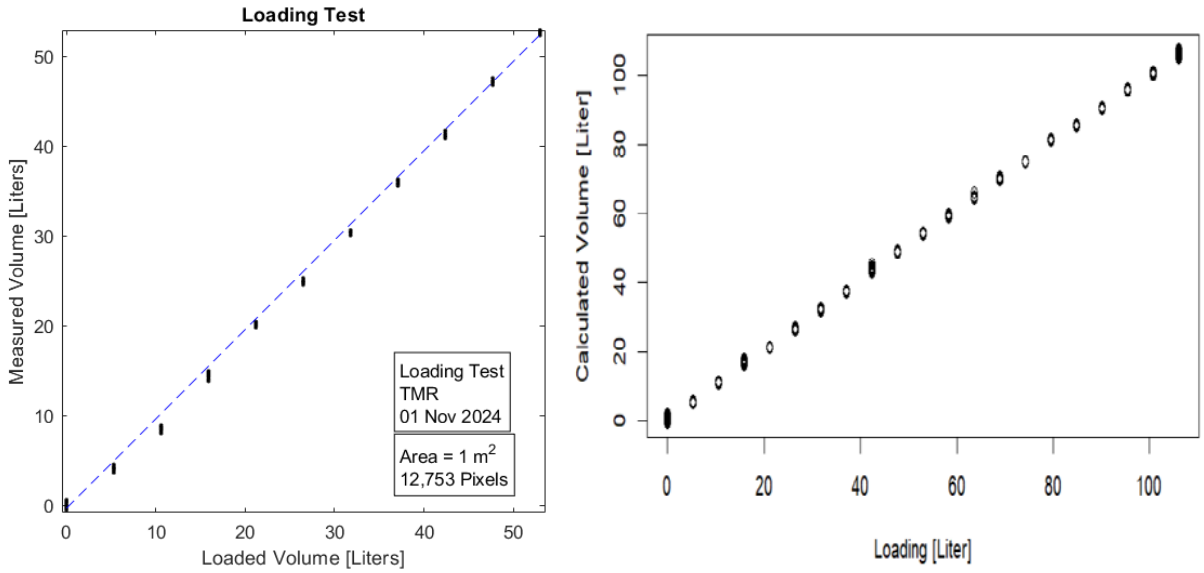
בוצע תיקוף לדיוק המדידה הנפחית. בניסויים מבוקרים, בהם כמויות מזון מדודות הוצבו ו/או הוסרו מהאבוס באמצעות דלי מדידה בנפח של 5.3 ליטר, המערכת הראתה דיוק גבוה. היסטוגרמת שגיאות המדידה הראתה התפלגות נורמלית עם ממוצע אפס ושגיאת תקן של 13 מ"מ, המעידה על דיוק וחזרתיות (repeatability) גבוהים. כמו כן, הודגם שהמערכת מסוגלת להבחין בין צריכת מזון בפועל (הסרת חומר) לבין הזזת מזון ממקום למקום באבוס (סכום אפס), יכולת קריטית למניעת טעויות מדידה בתנאי שטח.

לצורך אימות נוסף של דיוק המדידה הנפחית הוצב משטח שקילה אלקטרוני (שטח של כ-1 מ"ר) בעמדת האכלה, אל מול המצלמה. המשטח הועמס בכמויות מדודות של מזון בעזרת דלי מדידה, עד לעומס כולל של 106 ליטר. לאחר תהליך אימון ראשוני פותחה טכניקה שאפשרה הדירות (repeatability) גבוהה של מילוי הדלי, עם סטיית תקן של 0.1 ליטר בלבד במילוי כלי המדידה.



איור 4. אימות הדירות ההעמסה הנפחית - משקל מדוד כנגד נפח בהעמסת המשטח.

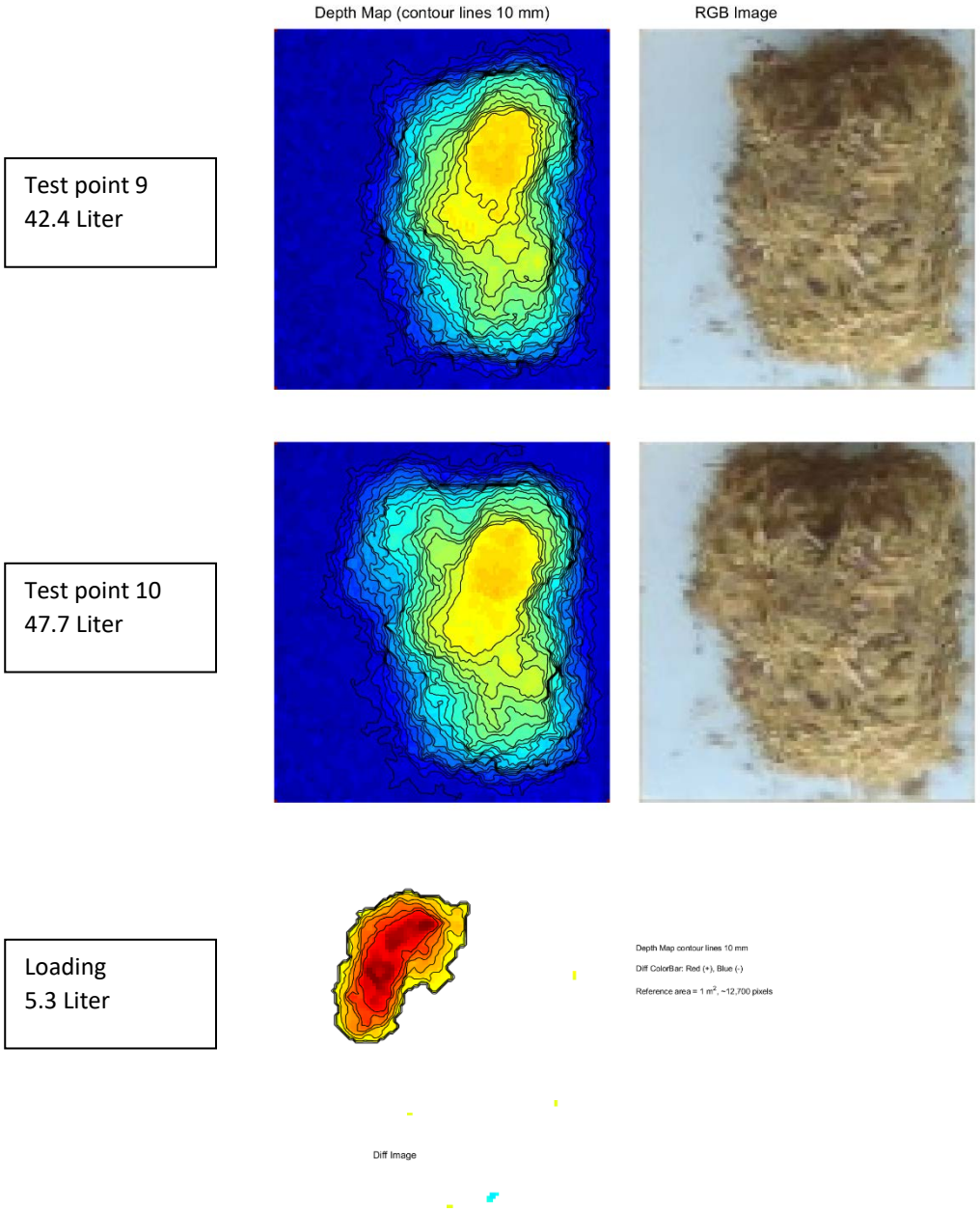
מהשוואת הנפח שנמדד על ידי המערכת כנגד הכמות שהועמסה בפועל נמצא כי רעש המדידה (measurement random error) - פיזור הקריאות ללא שינוי בנפח המזון - קטן מ-0.6 ליטר.



איור 5. אימות דיוק מדידת הנפח - נפח מדוד כנגד נפח בהעמסת המשטח.

מניתוח דיוקי המדידה כנגד נפח ההעמסה נמצא כי 95% מן המדידות נמצאו בתחום שגיאה הקטן מ-0.6 ליטר, ללא תלות בנפח הנמדד. כלומר, דיוק המדידה מושפע מרעש המדידה ולא מגודל הנפח הנמדד עצמו - תוצאה המעידה על יציבות המערכת על פני טווח רחב של כמויות מזון.

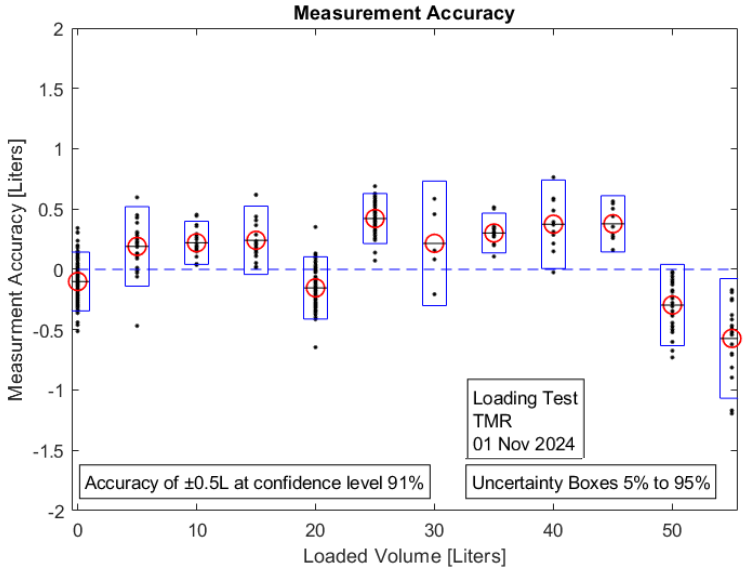
סודי מסחרי – בשלב מו"מ ב קידום מכון וולקני – לא לפרסום ולא להפצה. עותק יחיד נמסר למועצת החלב



איור 6. הדמיה חזותית בתהליך העמסת מזון בערך של 5.3 Liter בין 2 נקודות ניסוי

באיור 6 ניתן לראות כיצד המערכת מבצעת ניתוח של השינויים בין 2 נקודות ניסוי ומספקת מיפוי של אזור השינוי בכמות החומר.

סודי מסחרי – בשלב מו"מ ב קידום מכון וולקני – לא לפרסום ולא להפצה. עותק יחיד נמסר למועצת החלב



איור 7. ניתוח דיוק מדידה נפחי

באיור 7 ניתן לראות כי דיוק המדידה איננו מושפע מכמות החומר. הסטיות של הממוצע בכל נקודת ניסוי נובעת, בסבירות גבוה, מהקושי לוודא צפיפות מזון אחידה בכל מילוי של דלי המדידה.

מסקנות מאיורים 1-7:

מניתוח דיוקי המדידה כנגד נפח ההעמסה נמצא כי 90% מן המדידות נמצאו בתחום שגיאה הקטן מ-0.5 ליטר, ללא תלות בנפח הנמדד. המערכת אשר פותחה מאפשרת איסוף נתונים ממוכן של צריכת המזון הפרטנית, בתנאי תפעול מסחרי.

6.1 מודלים חישוביים לזיהוי פרות ולשקילת ארוחות

מעבר לאימות הדיוק הנפחי, פותחו ואומתו במסגרת המחקר גם מודלים חישוביים המבוססים על למידת מכונה, המאפשרים לתרגם את נתוני הנפח הגולמיים לתובנות ברמת הארוחה הבודדת ולזהות את הפרה הניזונה. עיקרי הממצאים (מפורטים במלואם במאמר המדעי המצורף כנספח א'):

- **זיהוי פרות בעמדת האכילה:** אלגוריתם היזוי המבוסס על YOLOv8 לזיהוי פרות בעמדת האכילה השיג דיוק (mAP50) של 0.95, ברמת דיוק התואמת עבודות מובילות בתחום.
- **מודל לחיזוי משקל ארוחה:** ניתוח נתונים מ-56 פרות חולבות מזן הולשטיין, לאורך 36 ימי ניסוי ו-365 ארוחות, הראה כי מודל Gradient Boosting - המשלב את נתוני הנפח עם נתוני צפיפות מזון ונתונים סביבתיים (טמפרטורה, לחות, רוח ולחץ ברומטרי) - חוזה את משקל הארוחה הבודדת בדיוק של MAE (Mean Absolute Error) 1.54 ק"ג ומקדם התאמה של R^2=0.88.
- **חוסן המודלים:** ניתוחי רגישות (sensitivity analysis) שבוצעו למודלים אישרו את חוסנם גם בתנאי שונות נתונים ורעש מדידה, ואת יכולתם לתפקד באופן יציב גם עם כמות מוגבלת יחסית של נתוני אימון.

- **דינמיקת צפיפות המזון:** נמצא כי צפיפות המזון שאינו נגיש לפרות עולה בהדרגה לאורך היום ומתייצבת לעת ערב, בעוד שצפיפות המזון הנגיש יורדת עקב ברירת מזון סלקטיבית של הפרות (העדפת רכיבים כבדים יותר כגון גרעיני תירס). ממצא זה מדגים את החשיבות של שילוב דינמיקת צפיפות המזון במודלים לחיזוי צריכה.

6.2 טבלת ריכוז תוצאות מרכזיות

הטבלה הבאה מרכזת את מדדי הביצועים העיקריים של המערכת, כפי שנמדדו ואומתו בשנת המחקר השנייה:

ערך שנמדד	מדד
18 עמדות (3 מצלמות, 6 עמדות למצלמה)	כיסוי עמדות אכילה
שגיאה קטנה מ-0.6 ליטר	דיוק מדידת נפח (95% מהמדידות)
13 מ"מ	שגיאת תקן של מדידת עומק
0.1 ליטר	סטיית תקן במילוי כלי כיול
0.95	דיוק זיהוי פרה בעמדה (YOLOv8, mAP50)
1.54 ק"ג (R^2=0.88)	דיוק חיזוי משקל ארוחה (Gradient Boosting, MAE)
56 פרות, 36 ימים, 365 ארוחות	היקף נתוני האימות
פעולה רציפה 24/7 ללא תקלות	זמינות המערכת בשטח

7. מסקנות

- דיוק המדידה הנפחית עומד על כ-0.6 ליטר ב-95% מן המדידות, ללא תלות בכמות המזון הנמדדת.
- המערכת שפותחה מאפשרת איסוף נתונים ממוכן של צריכת המזון הפרטנית, בתנאי תפעול מסחרי מלאים, תוך אפשור עדכון אלגוריתמים בשליטה מרחוק.
- המערכת פעלה ברציפות (24/7) ללא תקלות במהלך תקופת ההרצה ברפת מכון וולקני, עם שלוש מצלמות בפעולה מקבילה המכסות 18 עמדות אכילה.
- פותח ואומת בנפרד, במסגרת עבודת תואר שני, מודל להמרת נתוני הנפח הנמדדים למשקל חומר יבש (Dry Matter) בעזרת מודלים מבוססי למידת מכונה, המשלבים גם נתוני צפיפות מזון ונתונים סביבתיים (מפורט במאמר המדעי המצורף כנספח א').

8. סיכום הפרויקט וסיום הפעילות במכון וולקני

דוח זה מסכם שנת מחקר שנייה, שהיא גם שנת הפעילות האחרונה של המחקר במסגרתו הנוכחית במכון וולקני: החוקר הראשי מסיים את עבודתו במכון בחודש הקרוב, ולפיכך שנת מחקר שלישית לא תתבצע במתכונת שתוכננה.

חשוב להדגיש כי אין בכך כדי לפגוע בהישגי המחקר: במהלך שתי שנות הפעילות פותחה, הותקנה ואומתה מערכת מקורית ופונקציונלית למדידת צריכת מזון פרטנית ברפת מסחרית, המבוססת על חישה מרחוק בלבד וללא צורך בתשתית מכנית יקרה. המערכת הודגמה בהצלחה בתנאי שטח מלאים, לרבות פעולה רציפה על פני עמדות אכילה מרובות, וממצאי הדיוק שלה תואמים ואף עולים על תוצאות שדווחו במחקרים דומים בספרות המדעית (מפורט במאמר המצורף, נספח א').

כפוף למגבלות מסחריות הנהוגות במכון וולקני, קוד המערכת והנתונים ששימשו לפיתוח המודלים פתוחים וזמינים לציבור המחקר (ר' "Data availability statement" במאמר המצורף), כך שההמשכיות המדעית של הפרויקט מובטחת גם מעבר לסיום הפעילות במכון וולקני.

9. המלצות להמשך המחקר

תוכנית העבודה המקורית לשנה ג' כללה ארבעה יעדי המשך, אשר לא ימומשו במסגרת הנוכחית אך מומלץ לשקול את המשכם על ידי גורם מחקרי או מסחרי ממשיך:

- **אינטגרציית זיהוי ביומטרי פרטני שפיתחנו לפני הפרויקט:** שילוב מודול זיהוי ביומטרי אוטומטי (מבוסס RGB/IR ולמידת מכונה) שישייך כל מדידת צריכת מזון לפרה ספציפית - תנאי הכרחי ליישומים ניהוליים.
- **מודל המרה לחומר יבש:** השלמת הכיול והתיקוף של מודל ההמרה ממדידת נפח למשקל חומר יבש (DM) על פני הרכבי מנה ותנאי לחות משתנים (פותח ותואם ראשונית בעבודת המוסמך המצורפת כנספח א').
- **איסוף נתונים ארוך-טווח ובסיס נתונים:** הפעלה רציפה לאורך תקופה ארוכה והקמת בסיס נתונים מאובטח, לצורך היתוך (fusion) עם נתוני תנובת חלב, הרכב חלב, בריאות והתעברות.
- **מערכת תומכת החלטה:** פיתוח אב-טיפוס למערכת תומכת החלטה (DSS) שתספק התראות אוטומטיות על חריגות בצריכת מזון ותתמוך בקבלת החלטות ניהוליות וגנטיות.

לאור בשלות הטכנולוגיה ותוצאות האימות החיוביות, המערכת מוכנה, מבחינה טכנולוגית, לחיבור לגורם מייצר ומשווק מסחרי, ולשיתופי פעולה עם גופים ענפיים (כגון החקלאית, שיאון, התאחדות מגדלי הבקר, מרכזי מזון וגופי הדרכה), אשר יכולים להוביל את המשך הפיתוח וההטמעה המסחרית של הטכנולוגיה.

צוות המחקר ישמח לסייע לכל גורם ממשיך - אקדמי, ענפי או מסחרי - במסירת הידע, הקוד והנתונים שנצברו, על מנת להבטיח כי ההשקעה שנעשתה בשתי שנות המחקר ולפניו תניב ערך מלא גם בטווח הארוך.

10. הפצה מדעית ותודות

ממצאי המחקר גובשו לכדי מאמר מדעי מלא, המצורף לדוח זה כנספח א' (בשלבי סקירה בכתב עת מדעי בתחום ה-Precision Livestock Farming).

המחקר נתמך במענקים מהמדען הראשי של משרד החקלאות ("קנדל"), קרן המחקרים של מועצת החלב, מענקי השוק האירופאי TechCare ומענק אירופאי smart. תודה לצוות המחקר ולצוות רפת המחקר של מכון וולקני על הסיוע והתמיכה לאורך העבודה.

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נספח א'

המאמר האחרון על ההמרה מ נפח ל חומר יבש. In the review process

A 3D computer vision system and predictive models for individual feed intake measurement in dairy cows

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Abstract

Feed expenditures comprise up to 84% of dairy farm expenses, and inefficient utilisation of feed increases greenhouse gas emissions. Improving feed efficiency is crucial for farm profitability and sustainability. Advances in computer vision and 3D imaging technologies offer promising opportunities for non-invasive, continuous monitoring of feed intake. Yet early camera-based feed intake monitoring systems do not consider varied feed density.

An outdoor 3D computer vision system for feed intake measurement was developed and validated in a commercial research farm. The system included a Zed 2i 3D camera set at a

height of 4 m, in outdoor conditions. It utilised YOLOv8 with an mAP50 of 0.95 for cow detection and machine learning models, incorporating feed density and environmental factors, for feed intake estimation.

Analysis of data from 56 Holstein cows over 36 days, encompassing 365 meals, with various models found the Gradient Boosting model to achieve a mean absolute error (MAE) of 1.54 kg (with relative 61.62% error) and R^2 of 0.88 for meal weight prediction. Sensitivity analyses confirmed the model's robustness to data variability. Analysis of feed density dynamics showed that inaccessible to cows feed density increased steadily during the day, stabilising by evening, while accessible feed density declined due to selective eating of heavier components like corn grains.

This work demonstrated the system's ability to accurately measure individual feed intake in outdoor conditions. These findings will ultimately drive improvements in breeding programmes and reduction of the environmental footprint of dairy farming. The setting of the camera at 4 metres high enables tractor passage and a larger camera field of view of multiple feed positions along the feed lane.

Keywords: *Feed intake measurement, 3D camera, Precision Livestock Farming (PLF), Machine Learning in agriculture*

1. Introduction

The dairy industry faces significant challenges in balancing between its economic viability and environmental sustainability. Feed costs account for up to 84% of total dairy farm cost [1], and inefficient feed utilisation contributes to increased greenhouse gas emissions [2]. Studies have shown that improving feed efficiency can significantly reduce the carbon footprint of milk production [3]. Breeding for improved feed efficiency has been proposed as a sustainable long-term strategy to address these environmental issues, while maintaining or improving productivity [4]. Identifying high-performing individuals, with high milk production (liters per day, % fat, protein) alongside cost-efficient food consumption [5], is crucial for selective breeding programmes aimed at developing more efficient herds [6]. However, research systems for accurate measurement of individual feed intake are typically impractical for commercial settings. Traditional methods often rely on labour-intensive observations or expensive mechanical systems that require frequent maintenance [7].

Recent advancements in computer vision and 3D imaging technologies offer promising opportunities for non-invasive, continuous monitoring of feed intake [8]. A point cloud represents a set of data points in a 3D space, and can be exploited to provide a detailed spatial representation of feed volume, to estimate meal weight [9–13]. This approach, relies on remote imaging instead of measurement using mechanical devices, s, potentially reducing maintenance requirements and improving the long-term reliability of the system.

Several studies, including those by Saar et. al. [9], Bloch et. al.[10] and Bezen et. al. [13], developed camera-based feed intake measurement systems for outdoor environments, which are challenged by sunlight, temperature, and wind. None of the systems included environmental parameters, such as temperature, barometric pressure and wind, in the feed intake models. The different systems [13][9][10]employed cameras at different heights (97 cm, 1.3 m, 1.8 m) to monitor a single type of feed during a single season, yielded measurements with mean absolute errors (MAEs) of 0.127 kg, 0.14 kg and 1.24 kg, respectively. In contrast, when [11]employing a semi-indoor, multi-position system, with an independent camera dedicated to each position, Wang et. al. [11] reported on an MAE of 0.1 kg. However, results were reported for a single season and did not account for environmental factors. Indoor multi-position systems were used to measure a percentage MAE (MAE-percent) for daily feed intake [12] and repeatability estimates for daily feed intake [8].

The nutritional composition and physical characteristics of feed play a pivotal role in dairy cow feed consumption patterns. Different types of feed have varying densities, moisture content and nutrient concentrations, which influence animal preferences [14]. Incorporating feed density into prediction models not only enhances their accuracy but also provides deeper insights into feeding behaviours, which are critical for optimizing feed management strategies.

The application of machine-learning techniques to process agricultural data has shown great potential in recent years Mirani et. al. [15]. For example, these techniques have been used to predict various traits and behaviours, including feed intake in livestock farms [8,12].

Previous studies employed radiofrequency identification (RFID) tags to detect cow entrance to feeding stations [7,11,13] or used computer vision to identify cows by full body (Lassen et al., 2023; Lassen et al., 2018), reading the number on the neck [7,13] or ear [17,18] tags. Several works detected cow heads from

the side view, Hao et. al. [19] employed YOLOv5 and Pretto et. al. [18] used YOLOv3, both with an mAP50 of 0.95.

This study presents a 3D computer vision system that utilises point cloud data to non-invasively measure individual cow feed intake in an outdoor setting. The system integrates advanced 3D data processing, machine-learning models and environmental data to provide accurate, multi-position feed-consumption measurements, with adaptability to sunlight conditions and feed density. The camera was placed at 4.0 metres providing an automated system that enables to collect accurate data from multiple positions. The system includes two novelties: adaption to variable sunlight conditions and feed densities. The adaption to varying sunlight conditions in this paper was achieved using two methods: 1. Including highly variable data in the training process. 2. Develop a dynamic baseline depth model to account for variations in the empty surface depth due to the changing sunlight. The adaptation to feed density was achieved by developing feed intake prediction model and inaccessible feed volume and weight decrease models that take into account also environmental factors. The results show how cows' preference for highly nutritious feed, particularly heavier components such as maize grains and cereals, affects the density change of the consumed feed compared to unconsumed feed. By enabling precise identification of efficient cows, this system can improve breeding programs and contribute significantly to reducing the environmental footprint of dairy farming. In addition, automated collection of detailed, individual-level data on feed intake promises to open up new opportunities for precision livestock farming (PLF) [20]. In addition, the diverse bid data collected will set the stage for future research into previously unidentifiable patterns relating to cow behaviour, nutrition and breeding.

The research aimed to develop a 3D model to measured individual food intake under outdoor conditions. The specific objectives were to:

1. Develop a computer vision system using 3D cameras to detect cows and calculate feed volume.
2. Develop a dynamic baseline depth model to account for variations in the empty surface depth due to factors such as changing sunlight
3. Create and validate predictive models to estimate individual cow meal weight based on feed volume reduction and environmental factors.

2. Materials and Methods

2.1 Experimental Setup

This study was conducted in an outdoor research cowshed at the Volcani Institute between June and August 2023 and involved 56 Holstein cows. The setup was designed to capture comprehensive data on feed intake and environmental conditions. Two weight-scales were positioned beneath the camera, in the feed lane (Figure 2). One weight-scale was positioned out of cows' reach, to measure changes in density of inaccessible feed. The 2nd weight scale was within cows' reach, to provide ground truth of the actual feed intake. . Both weight-scales were equipped with 1000 kg loadcells with 15-cm-high barriers, offering 0.023% precision (SQB, Keli CEE, Poland). The scale was housed within robust metal frames secured to the ground and positioned on rubber bases for level positioning. The total mixed ration (TMR) ingredients are detailed in Appendix B.

2.2 Data Collection System

A Zed 2i 3D camera system (Stereolabs, France) was mounted 4 m above the cowshed floor, positioned parallel to the ground and facing downward in a z-down orientation (Figure 1). This height was chosen to

allow full view of multiple feeding stations while providing ample room for the feed mixer wagon to pass below the camera.

An Arduino Uno microcontroller board (Arduino, Italy) paired with a HX711 amplifier (Adafruit, USA) was connected to the scale for data acquisition. Two floodlights (Nisko, 200 W, 1800 lumens, 6000 K, beam angle of 130°) were installed to ensure consistent illumination throughout the day and night. Weight measurements, point cloud capture, and RGB images were collected at 20-s intervals.

Environmental data in the cowshed were collected using an Arduino Uno coupled with a BME280 sensor (Bosch Sensortec, Germany), capturing the temperature, humidity and pressure every 2 min. Additional weather data (wind speed and direction, pressure, temperature, humidity) were obtained from the Israel Meteorological Service Centre in Bet Dagan, located 2 km from the cowshed, where measurements are taken every 10 min.

All devices were interconnected with a Jetson Xavier NX device (NVIDIA, USA), which managed data collection using a Python script.

2.3 Cow Detection

The YOLOv8 object-detection algorithm, utilizing bounding boxes, was employed for cow detection [21]. The model was trained on a dataset of 249 images collected from 20 January to 23 January 2023, covering various cow poses and lighting conditions throughout the day. Images were annotated, with bounding boxes encircling the entire head and ears of the cattle.

The dataset was randomly split into training (70%, 174 images), validation (20%, 49 images) and testing (10%, 26 images) sets. Each image of the training set was first pre-processed by applying auto-orientation and resizing (to 640x640 pixels) to ensure consistency. After pre-processing, augmentation techniques, including rotation (± 45˚), brightness adjustment (± 40%) and blurring (≤ 0.75 pixel), were applied on the training data, to improve the model robustness. Each image was augmented using all of the techniques, resulting in three variations per image (the original image and two augmented images). This increased the train-set from 174 to 522 images (Table 1). Three model variations were trained: YOLOv8n (nano), YOLOv8s (small) and YOLOv8m (medium).

2.4 Feed Volume Calculation

2.5 2.4.1 Dynamic Baseline Model

Accurately measuring feed volume in outdoor conditions requires accounting for variability in sunlight, which affects the apparent depth of the empty scale as captured by the camera. To address this challenge, a dynamic baseline depth model was developed to predict the baseline depth under varying sunlight conditions (Figure 5).

Model Development

Measurements were collected from an empty weighing scale over a continuous 43-h period (July 4–6, 2023). To mitigate noise and capture underlying trends, the data were smoothed using the locally weighted scatterplot smoothing (LOWESS) function, with a fraction value of 0.05 (Cleveland, 1979). The smoothing process was crucial for identifying trends across time of day rather than relying on individual, potentially noisy measurements.

To generalize the model while maintaining precision, a grid search was conducted to optimize the parameters for ridge regression. The best-performing model used a polynomial transformation of degree 16 and an alpha value selected for its balance between overfitting and underfitting.

The smoothed depth measurements were ordered by time of day, regardless of the date, to develop a time-dependent predictive model. This approach ensured that the model accounted for daily sunlight variations rather than seasonal anomalies.

Model Application

The dynamic baseline depth model was integrated to provide real-time depth adjustments. After each image capture, the time of day was input into the model to retrieve the predicted baseline depth. This value was then used to calculate the feed volume by measuring the difference between the baseline depth and the observed depth of the scale filled with feed.

Validation and Limitations

The model's performance was evaluated by MAE and R^2 metrics. Results confirmed its effectiveness under typical summer conditions in Israel, characterized by consistent sunlight and minimal cloud cover. However, as this study served as a proof of concept (POC), the model was not retrained during the experiment. Future work will include periodic retraining to adapt to seasonal variations and changes in sunlight conditions over time.

2.6 Calculation steps

Feed volume was calculated as follows (Figure 3):

1. Point Cloud Processing: Point cloud data were recorded at 20-s intervals. Each frame was cropped to include only the area within the scale, with a 5 cm margin to mitigate the influence of noisy points near the edges.
2. Depth Extraction: z-values were extracted from the cropped point clouds to measure the depth of specific points in space. These values were then averaged to determine the mean depth of the area of interest (Figure 4).
3. Dynamic Baseline Model: The capture time of each image was input into the dynamic baseline model to retrieve the predicted depth of the empty scale at that specific time. This predicted baseline depth was then used to adjust the measured depth of the feed scale, accounting for sunlight-induced variations. By incorporating this time-sensitive adjustment, the feed volume calculation achieved greater accuracy under outdoor conditions.
4. Volume Calculation: The actual feed depth was computed as the difference between the measured depth and the baseline depth provided by the regression model. The feed volume was calculated by multiplying this depth by the dimensions of the weight scale (140 × 105 cm).

2.7 Data Preparation

2.7.1 Meal Weight Prediction Task

The following approach was adopted for meal weight prediction:

Meal Definition: A meal was considered to have started when two consecutive images showed a cow's presence at the feeding station, and ended when two consecutive images showed no presence.

Weight Measurement: The initial weight was calculated by averaging the last three measurements before the meal, while the final weight was determined by averaging the first three measurements after the meal.

Feature Engineering: For each meal, the following features were calculated:

Meal volume: The mean volume of the last three measurements before the meal minus the mean of three volume measurements after the meal.

Meal duration: Time elapsed between the start and end of a meal.

Time since start of feeding day: mMinutes elapsed from the start of the feeding day (11:00 AM or actual feeding time, whichever was later) until the start of the meal.

Weather data: Average and sum of various weather parameters from the start of the feeding day until the meal start, including barometric pressure, relative humidity, temperature (mean, max, min, surface), wind direction and speed and rainfall.

2.7.2 Inaccessible Feed Volume and Weight Decrease Tasks

2.7.2.1 Time Frame Segmentation

The dataset was segmented into 2-h time frames to facilitate a detailed analysis of the variations of the inaccessible feed weight and volume (Figure 6). Each subsequent frame commenced ten minutes after the preceding frame, enabling a continuous data stream. This segmentation allowed the capture of nuanced changes in environmental conditions and feed metrics throughout the day.

2.7.2.2 Mean Calculation for Weather and Feed Metrics

The average of the weather measurements taken throughout the entire duration of each time frame was calculated. Similarly, for feed-related measurements, the mean of the first and last 15 recordings, equivalent to the initial and final five minutes of each frame, was calculated. This strategy aimed to reduce noise in the data by focusing on stable periods, thus minimizing the influence of transient fluctuations in the feed weight and volume.

2.6 Model Development

Several regression models were developed to predict meal weight:

- Linear Regression Models (including forward and backward stepwise regression) - Served as baseline models owing to their simplicity and interpretability. These models were evaluated with and without feature-selection techniques, to assess the impact of variable reduction on performance.
- Decision Tree, Random Forest and Gradient Boosting Models – Selected for their capacity to capture non-linear relationships without requiring transformations of the input data. Their structure allows for interpretation of how different features affect the predicted outcome, thereby providing valuable insights beyond mere prediction.

Hyperparameter tuning was performed using a grid search with 10-fold cross-validation.

Model selection was based on MAE for meal weight prediction task and MAE% for weight decrease and volume decrease tasks, with respect to R^2, and mean error (ME).

For meal weight prediction, the error was measured in kg of feed per meal.

For the inaccessible feed weight decrease and volume decrease prediction tasks, errors were measured as the percentage of decrease in volume and weight over a 2-hour time frame.

2.7 Sensitivity analyses

The following sensitivity analyses tests were performed:

- 10-fold cross-validation to evaluate performance across different data subsets
- Maximal test-set size analysis to determine model stability with varying amounts of train data
- Random noise tests to evaluate the resilience of the model to data perturbations

2.8 Feature Importance

Feature importance was quantified using permutation importance analysis to provide insights into the contribution of each feature to model performance. This method measures the decrease in the model's predictive performance when a specific feature's values are randomly shuffled, breaking the relationship between that feature and the target variable. The importance of each feature is expressed as the change in the MAE after shuffling, with larger drops indicating a more influential feature.

3. Results

3.1 Data Analysis

3.1.1 Density analysis

Density of inaccessible feed (Figure 7) exhibited a steady increase from start of the feeding day at 11:00 until approximately 20:00, before reaching a stable phase. This trend can be attributed to the deflation of inaccessible feed and the retention of moisture, which slows down volume reduction compared to weight loss. The formation of a protective mantle prevents water evaporation, maintaining density levels.

Conversely, feed density in the accessible position showed a consistent decline as cows selectively chose heavier feed components like maize grains and cereals. This selective behaviour caused the volume of accessible feed to decrease more rapidly than its weight, leading to a density drop. Towards the end of the feeding period, density values were less stable, likely due to the challenges of calculating density with low feed weight and near-depletion volumes. These findings underscore the influence of cow feeding preferences on feed characteristics and the variability in feed properties over time.

3.1.2 Meal analysis

All meals were initially collected from the raw data. Meals with overlapping time periods or those occurring less than 10 seconds apart were combined into a single unified meal. Feed volume and weight for each meal were then calculated as the difference between the weight and volume measurements taken immediately before and after the unified meal.

After initial pre-processing, meals were selected as the dataset for model training and evaluation based on the following criteria:

- Volume > 0.1 L
- Weight 1<X<50 kg.
- Z-score within ±3 of the dataset means

This resulted with 365 meals used for the analysis, with weights ranging from 1.01 kg to 29.67 kg.

3.2 Cow Detection Performance

The YOLOv8s model achieved best precision (0.96), a recall of 0.93 cow presence detection and an mAP50 of 0.95 as compared to 0.93 for both YOLOv8n and YOLOv8m (Table 2).

3.3 Meal Weight Prediction Task

3.3.1 Meal Weight Prediction Task - Model Selection

In total, the data from 365 meals, weighing 6.01± kg (range: 1.01-29.67 kg), were used for the analysis. Following fine-tuning, the dataset was divided into training and test sets (80%/20%), and the models were evaluated to predict meal weight on the test set (Figures 8 and 9). Most tree-based models performed well (Table 3), with the Gradient Boosting and Random Forest achieved an R^2 of 0.880 and 0.876 and an MAE of 1.546 kg and 1.537 kg, respectively. Decision Tree performed somewhat less effectively, with an R^2 of 0.686 and an MAE of 2.090. Linear Regression with backward-stepwise selection achieved an R^2 of 0.646 and an MAE of 3.015. The least effective models were basic Linear Regression, with an R^2 of 0.605 and an MAE of 3.121, and Linear Regression with forward stepwise selection, with an R^2 of 0.577 and an MAE of 3.157. These results emphasize the limitation of linear models, even with feature selection. All ME values were smaller than e-14, indicating that the errors are centralized around zero.

3.3.2 Meal Weight Prediction Task - Sensitivity Analysis

The 10-fold cross-validation of the Gradient Boosting model achieved a mean R^2 value of 0.880 (std = 0.034) in meal weight prediction (Appendix E and Appendix F). The model demonstrated stable performance even with decreased training set sizes (with 10% differences), maintained R^2 above 0.8 and MAE below 2.0 kg, until the training was performed only with 20% of the data (80% test-set size) which resulted in an MAE of 2.51 kg and an R^2 of 0.7301. (Appendix G).

In random noise tests, the Gradient Boosting model showed resilience to data perturbations. Even when 10% random noise was added to the target variable, the model maintained an MAE of 1.820 kg, indicating high robustness (Appendix H).

3.3.3 Meal Weight Prediction Task - Feature Importance

Analysis of feature importance revealed that meal volume was consistently the most significant meal weight predictor across all the models. For the Gradient Boosting model, the top features were:

- Meal volume (importance: 0.38)
- Mean temperature (importance: 0.15)
- Mean pressure (importance: 0.14)

Full results are detailed in Appendix C and selected parameters in Appendix I.

3.4 Inaccessible Feed – Volume Decrease Task

3.4.1 Volume Decrease Task – Model Selection

As shown in Table 4, tree-based models outperformed linear models in predicting volume decrease. The Random Forest and Gradient Boosting models achieved R^2 values of 0.973 and 0.970, with MAE% of 0.0044 and 0.0049, respectively. The Decision Tree model also performed well, with an R^2 of 0.910 and an MAE% of 0.0080. In contrast, linear models displayed limited effectiveness in capturing the non-linear relationships within the data, as indicated by lower R^2 values (approximately 0.51) and higher MAE% scores (around 0.023).

Among the regularized linear models, Elastic Net demonstrated slightly better performance than Ridge and Lasso regression, with an R^2 of 0.511 and an MAE% of 0.0230. PCA Linear Regression models with reduced feature sets did not achieve acceptable performance, emphasizing the limitations of linear approaches even with dimensionality reduction. Overall, tree-based models, particularly Random Forest and Gradient Boosting, emerged as the most suitable for volume decrease prediction, with high accuracy and robustness to complex feature interactions.

3.4.2 Volume Decrease Task – Sensitivity Analysis

The 10-fold cross-validation of the Gradient Boosting model achieved a mean R^2 value of 0.970, with stable performance across folds (std = 0.008) (Appendix E). Evaluation of sensitivity to training-set size showed that the models maintained R^2 values above 0.8 and MAE% below 0.014 for up to a 70% test-set size. At a test-set size of 90%, Gradient Boosting retained an R^2 of 0.631 and an MAE of 0.0192, highlighting the model's robustness even with reduced training data (Appendix K).

Random noise tests further confirmed the model's resilience. With 10% random noise added to the target variable, the Gradient Boosting model maintained an MAE% of 0.0050, showcasing its capacity to withstand variability in environmental data collection (Appendix N).

3.4.3 Volume Decrease Task – Feature Importance

Feature importance analysis for the volume decrease models highlighted the role of environmental factors, with both Gradient Boosting and Random Forest models identifying key predictors:

- **Time Since Start:** In the Gradient Boosting model, the time elapsed since the start of the feeding day was the feature of the highest importance to volume decrease prediction (0.301). It contribution to explanation of volume decrease patterns was likely due to daily cycles in environmental conditions.
- **Wind Speed (Ws10mm):** This feature was more prominent in the Random Forest model (importance: 0.145), as wind directly impacts the feed drying rate. Higher wind speeds generally accelerate the evaporation of moisture from the feed surface, contributing to volume decrease.

3.5 Inaccessible Feed – Weight Decrease Task

3.5.1 Weight Decrease Task – Model Selection

Tree-based models displayed superior accuracy in predicting weight decrease of inaccessible feed, with Gradient Boosting and Random Forest models achieving R^2 values of 0.974, accompanied by low MAE% of 0.0021 and 0.0020, respectively. Decision Tree performed moderately well, reaching an R^2 of 0.883 and an MAE% of 0.0037, yet was outperformed by ensemble methods (Table 5). Linear models, including Ridge and Lasso, showed limited effectiveness, with R^2 values of approximately 0.42 and MAE% values of approximately 0.013. PCA-based linear models, even with optimized component selection, provided reduced predictive power.

3.5.2 Weight Decrease Task – Sensitivity Analysis

In 10-fold cross-validation, Gradient Boosting showed a mean R^2 of 0.974 with minimal variation, demonstrating stability. Varying test-set sizes yielded consistent results, with R^2 values above 0.8 and

MAE% below 0.006 for test sizes of up to a 70%, dropping to R^2 of 0.761 at a 80% test size. Noise robustness tests confirmed that MAE% remained low at 0.0026 even with 10% random noise.

3.5.3 Weight Decrease Task – Feature Importance

In both Gradient Boosting and Random Forest, critical predictors of weight decrease of inaccessible feed included:

Time Since Start: Most significant in Gradient Boosting (0.250) and high in Random Forest (0.212), reflecting the importance of elapsed time since feeding start.

Surface Temperature: Key in both models, with importances of 0.252 (Gradient Boosting) and 0.249 (Random Forest), affecting feed weight through temperature-related moisture dynamics.

4. Discussion

Density Analysis: Feed density analysis revealed distinct patterns between accessible and in accessible feed, with the density of inaccessible feed increasing throughout the day, stabilizing at around 20:00, while accessible feed density decreased due to selective eating. These findings align with physiological feeding behaviours and environmental interactions. Unstable density calculations near feed depletion highlight the challenges of precision modelling under such conditions.

Meal Weight Prediction: The Gradient Boosting model achieved the best performance, with an MAE of 1.54 kg and an R^2 of 0.88. This accuracy is notable, given the environmental variability and the 4-m camera height, which reduced resolution by 900% (0.01 cm at 1.5 m height to 0.1 cm at 4 m height). Previous studies, such as Bezen et al. (2020) and Saar et al. (2022), reported MAEs of 0.127–0.14 kg under controlled indoor or semi-indoor conditions, highlighting the trade-offs of the presented outdoor setup. The model accounted for environmental factors like temperature and pressure, improving adaptability compared to systems that ignored these variables.

Cow Detection: The YOLOv8 algorithm achieved a mAP50 of 0.95, comparable to other studies using side-view cameras (e.g., [19], [18]). The system's top-down camera configuration avoided the need for close-range sensors (e.g., RFID), which are prone to physical contact failures. This approach proved effective in identifying cows under challenging lighting conditions, ensuring precise detection of meal start and end times.

Volume Decrease: The Random Forest and Gradient Boosting models exhibited high accuracy in predicting feed volume reduction, with R^2 values above 0.97 and MAE% below 0.005. The steady reduction in inaccessible feed volume was influenced by environmental factors, such as wind speed, which accelerates moisture evaporation. These results align with the findings of Bloch et al. (2019), who highlighted the importance of environmental effects on feed stability.

Feed Weight Decrease: Feed weight reduction occurred more rapidly than volume reduction, reflecting animal preference for heavier feed components such as maize grains and cereals. The best models (Gradient Boosting and Random Forest) achieved R^2 values of 0.974 and MAE%s of 0.002 kg. Toward the end of feeding days, small meal sizes introduced instability in weight measurements, a limitation likely due to the lower precision of density calculations at near-depletion.

Limitations: A primary limitation of this study was its 36-day duration, capturing only the summer season. Seasonal variations in environmental factors, such as sunrise and sunset times, were not accounted for. Extending the study to at least 100 days and across multiple seasons would require recalibration of the baseline depth model to adapt it to varying sunlight conditions. Another limitation was the resolution loss due to the 4-m camera height, which introduced noise into the measurements. While this height enabled

scalability for multi-position monitoring and tractor clearance, higher-resolution cameras or multi-camera setups could mitigate this issue.

Future Research Recommendations: Future studies should incorporate seasonal data to examine how variations in environmental conditions affect feed intake patterns and system performance. Integration of cow identification methods (e.g., facial recognition) would enable individualized tracking and enhance the system's utility for genetic selection programs. Additionally, future research should explore the implementation of a multi-position setup, as the Zed 2i camera's 120° field of view can capture up to six feeding positions simultaneously. This capability could significantly enhance the system's scalability and utility in larger commercial farms.

5. Conclusions

This work developed a 3D computer vision system to estimate (a) diet density and (b) indvidual animal feed intake (meal). It appears that cows' preference for (heavier) nutritious components influences diet density changes, “consumed” versus “unattended feed. The findings emphasize the importance of incorporating feed density into predictive models to better understand eating behaviour.

For meal weight prediction, the Gradient Boosting model achieved an MAE of 1.54 kg and an R^2 of 0.88, suggesting high accuracy and robustness under outdoor conditions. For volume decrease of inaccessible feed, the Random Forest and Gradient Boosting models achieved high accuracy, with R^2 values above 0.97 and MAE% below 0.005. The reduction in inaccessible feed volume was influenced by environmental factors such as wind speed, which accelerates moisture evaporation. Weight decrease of inaccessible feed occurred more rapidly than volume reduction, reflecting cow preference for heavier feed components such as maize grains and cereals. The best models (Gradient Boosting and Random Forest) achieved R^2 values of 0.974 and MAE% of 0.002 for weight decrease prediction. The YOLOv8-based cow detection model achieved an mAP50 of 0.95, ensuring accurate meal event detection. The camera’s 4-m height enabled scalability and the potential to monitor up to six feeding positions simultaneously, making the system highly practical for real-world applications.

This work integrated feed density measurements, environmental data and cow detection into a robust system for precision livestock farming aimed at advancing feed efficiency and sustainability. Future studies should incorporate seasonal data and explore multi-position setups for broader applications.

Tables

Table 1: Images sets split

Dataset	Original images	Augmented Images	Total images
Training	174	348	522
Validation	49	0	49
Testing	26	0	26
Total	249	348	597

Table 2: YOLOv8 cow detection models comparison

mAP – Mean average precision

Model Size	Precision (B)	Recall (B)	mAP50 (B)	mAP50-95 (B)	Fitness	Preprocess Time (s)	Inference Time (ms)	Loss	Postprocess Time (s)
YOLOv8 n	0.9654	0.9375	0.9321	0.6501	0.6783	2.1923	12.08	0.0	0.6923
YOLOv8 s	0.9656	0.9375	0.9584	0.7340	0.7565	1.9996	16.85	0.0	0.6923
YOLOv8 m	0.9666	0.9040	0.9338	0.6874	0.7120	2.0385	20.52	0.0	0.6538

Table 3: Meal Weight Models Results

MAE (KG) – Mean absolute error in kilograms, ME – Mean error

Model	MAE (kg)	R^2	ME
Linear Regression	3.121	0.605	2.063e-15

Linear Regression (Forward Selection)	3.157	0.577	9.694e-15
Linear Regression (Backward Selection)	3.015	0.646	1.537e-14
PCA Linear Regression (All Features)	3.668	0.421	-9.149e-16
PCA Linear Regression (Forward Features)	4.506	0.091	-1.012e-15
PCA Linear Regression (Backward Features)	4.506	0.091	-1.012e-15
Ridge	3.189	0.576	3.698e-15
Lasso	3.192	0.569	3.075e-15
Elastic Net	3.193	0.570	2.530e-15
Decision Tree	2.090	0.686	-1.533e-16
Random Forest	1.537	0.876	9.879e-16
Gradient Boosting	1.546	0.880	-4.866e-18

Table 4: Volume Decrease Model Results

MAE (KG) – Mean absolute error in kilograms, ME – Mean error

Model	MAE	R^2	ME
Linear Regression	0.0232	0.510	-1.37e-18
Linear Regression (Forward)	0.0233	0.503	5.72e-18
Linear Regression (Backward)	0.0230	0.514	7.55e-18
PCA Linear Regression (All)	0.0243	0.454	2.51e-18
PCA Linear Regression (Forward)	0.0244	0.442	2.28e-18
PCA Linear Regression (Backward)	0.0243	0.454	3.89e-18
Ridge	0.0231	0.509	2.28e-19
Lasso	0.0231	0.511	1.14e-18
Elastic Net	0.0230	0.511	-1.60e-18
Decision Tree	0.0080	0.910	-1.14e-19
Random Forest	0.0044	0.973	8.78e-18
Gradient Boosting	0.0049	0.970	-4.09e-19

Table 5: Weight Decrease Model Results

MAE (KG) – Mean absolute error in kilograms, ME – Mean error

Model	MAE	R^2	ME
Linear Regression	0.0132	0.422	-1.57e-17
Linear Regression (Forward)	0.0136	0.407	1.03e-18
Linear Regression (Backward)	0.0132	0.426	-1.65e-17
PCA Regression (All)	0.0148	0.251	2.11e-18
PCA Regression (Forward)	0.0148	0.251	1.77e-18
PCA Regression (Backward)	0.0148	0.251	6.86e-19
Ridge	0.0131	0.422	-1.16e-17

Lasso	0.0133	0.415	-3.32e-18
Elastic Net	0.0133	0.416	-3.89e-18
Decision Tree	0.0038	0.883	2.68e-21
Random Forest	0.0020	0.974	3.67e-18
Gradient Boosting	0.0021	0.974	-2.77e-19

Appendices

Appendix A: Data and code

GitHub: https://github.com/benjika/research_code

Appendix B: Ingredients, chemical and structural composition, and mineral concentrations of TMR

Ingredients (% of TMR DM)	TMR
Wheat silage	20.0
Corn grain, ground	18.5
Wheat hay	15.8
Corn gluten feed	12.4
Dried distillers grains, golden	6.6
Soy meal	5.0
Rapeseed meal	4.5
Wheat bran	3.3
Barley grain, ground	3.1
Whey concentrate	2.3
Wheat hay	2.2
Cotton seeds	1.9
Calcium and sodium chloride	1.4
Palmitic acid	1.0
Ca-LCFA[1]	1.0
Sodium bicarbonate	0.7
Limestone	0.2
Urea	0.1
Vitamins and trace minerals[2]	0.045
Composition (% of TMR DM)	
DM (% of wet TMR)	70.9
OM	91.6
CP	18.1
Ether extract	6.24
αNDFom	34.0
ADF	18.2
Lignin	2.4
Starch	18.6
Ca	0.97
P	0.72

[1] Calcium salts of long-chain fatty acids

[2] Mix containing (g/kg of mix DM): Zn, 24; Fe, 24; Cu, 12.8; Mn, 24; I, 1.44; Co, 0.32; Se, 0.32; 16 MIU of vitamin A; 3.2 MIU of vitamin D3; and 48 KIU of vitamin E.SS

Appendix C: Meal Weight model selection results

Model	R2	Adj R2	MAE	MSE	RMSE	ME
Linear Regression	0.605328	0.558088	3.121468	15.746277	3.968158	2.063494e-15
Linear Regression (Forward Selection)	0.577623	0.561553	3.157399	16.806522	4.099576	9.694528e-15

Linear Regression (Backward Selection)	0.646116	0.625530	3.015634	14.544907	3.813779	1.537887e-14
PCA Linear Regression (All Features)	0.421252	0.351985	3.668883	23.665574	4.864728	-9.149454e-16
PCA Linear Regression (Forward Features)	0.091960	-0.016696	4.506888	38.737748	6.223966	-1.012280e-15
PCA Linear Regression (Backward Features)	0.091960	-0.016696	4.506888	38.737748	6.223966	-1.012280e-15
Ridge	0.576303	0.525585	3.189207	16.873846	4.107779	3.698716e-15
Lasso	0.569912	0.518428	3.192954	17.075605	4.132264	3.075774e-15
Elastic Net	0.570583	0.519179	3.193400	17.067329	4.131262	2.530700e-15
Decision Tree	0.686439	0.648909	2.090734	13.124602	3.622789	-1.533020e-16
Random Forest	0.876683	0.861926	1.537939	5.079333	2.253738	9.879464e-16
Gradient Boosting	0.880121	0.865776	1.546640	5.017110	2.239891	-4.866731e-18
Decision Tree (Decision Tree Feature Selection)	0.664159	0.656827	2.061109	13.190201	3.631832	2.180774e-01
Random Forest (Decision Tree Feature Selection)	0.880683	0.878077	1.512398	4.915933	2.217190	2.224096e-15
Gradient Boosting (Decision Tree Feature Selection)	0.869567	0.866718	1.565547	5.267672	2.295141	-1.539104e-16

Appendix D: Meals Weight models - Selected Parameters

Model	Hyperparameter	Best value

PCA Linear Regression (All Features)	n_components	8
PCA Linear Regression (Forward Features)	n_components	5
PCA Linear Regression (Backward Features)	n_components	5
Ridge	alpha	0.01
Lasso	alpha	0.00001
	max_iter	10000
Elastic Net	alpha	0.0001
	l1_ratio	0.9
	max_iter	10000
Decision Tree	criterion	friedman_mse
	max_depth	10
	max_features	None
	min_samples_leaf:	1
	min_samples_split	5
	splitter	random
Random Forest	bootstrap	False
	max_depth	None
	max_features	Sqrt
	max_leaf_nodes	50
	min_samples_leaf	1
	min_samples_split	2
	n_estimators	200
	min_impurity_decrease	0.01
Gradient Boosting	learning_rate	0.1
	max_depth	40
	max_features	log2
	min_samples_leaf	2
	min_samples_split	4
	n_estimators	300
Decision Tree (Selected Parameters)	criterion	absolute_error
	max_depth	40
	max_features	log2
	min_samples_leaf	2
	min_samples_split	10
	splitter	best
Random Forest (Selected Parameters)	bootstrap	False
	max_depth	10
	max_features	Sqrt
	max_leaf_nodes	50
	min_impurity_decrease	0.01
	min_samples_leaf	1
	min_samples_split	2
	n_estimators	200
Gradient Boosting (Selected Parameters)	learning_rate	0.1
	max_depth	5

	max_features	log2
	min_samples_leaf	2
	min_samples_split	2
	n_estimators	100

Appendix E: Meal Weight 10-fold cross validation results

Model	Mean R2	Std R2	Mean MSE	Std MSE	Mean MAE	Std MAE	Mean ME	Std ME
Linear Regression	0.605328	0.147339	15.746277	3.011766	3.121468	0.301115	-0.005242	0.385127
Linear Regression (Forward Selection)	0.577623	0.168999	16.806522	2.320348	3.157399	0.245548	0.031052	0.431516
Linear Regression (Backward Selection)	0.646116	0.088002	14.544907	2.337737	3.015634	0.294533	0.013962	0.410940
PCA Linear Regression (All Features)	0.421252	0.253653	23.665574	6.607652	3.668883	0.539306	0.005415	0.722953f
PCA Linear Regression (Forward Features)	0.469760	0.148647	22.120561	5.028581	3.627008	0.337855	0.000925	0.709443
PCA Linear Regression (Backward Features)	0.449651	0.172895	22.920807	5.454962	3.650935	0.434131	0.012878	0.663527
Ridge	0.576303	0.170333	16.873846	2.973158	3.189207	0.348935	0.013778	0.445581
Lasso	0.569912	0.184585	17.075605	3.294894	3.192954	0.373808	0.023861	0.422230
Elastic Net	0.570583	0.181772	17.067329	3.253247	3.193400	0.369458	0.023026	0.423730
Decision Tree	0.686439	0.178301	13.124602	8.176353	2.090734	0.660745	-0.311193	0.451967
Random Forest	0.876710	0.044398	5.077751	1.662152	1.537657	0.237926	-0.157506	0.342122
Gradient Boosting	0.880000	0.033704	5.021619	1.503423	1.548358	0.172772	-0.088505	0.333922
Decision Tree (Desicion Tree Feature Selection)	0.664159	0.320654	13.190201	12.026685	2.061109	0.595818	-0.052376	0.622639

Random Forest (Desicion Tree Feature Selection)	0.880683	0.043482	4.915933	1.646620	1.512398	0.254301	-0.105420	0.351914
Gradient Boosting (Desicion Tree Feature Selection)	0.869567	0.049785	5.267672	1.567875	1.565547	0.229515	-0.135496	0.425179

Appendix F: Meal Weight 10-fold cross validation full results

Model	R2	MSE	MAE	ME
Linear Regression	[0.58233662 0.40582568 0.31702027 0.65202842 0.74269905 0.69091528 0.76554717 0.47581791 0.69215668 0.72892998]"	[21.07158724 17.14375142 15.54240939 15.62145594 15.42189268 11.3366938 14.2920786 20.66816088 13.98916227 12.375576]	[3.67544654 3.22313103 3.21031171 3.06215471 3.25046598 2.68070878 2.94148513 3.46876443 3.03543935 2.66677668]	[0.33023074 -0.2484253 -0.19307372 -0.08632257 0.04300751 0.28000037 0.39920149 -0.88684679 0.46628094 -0.15646836]
Linear Regression (Forward Selection)	[0.60778711 0.4351771 0.12141335 0.66272446 0.66999401 0.64136103 0.7213745 0.60428069 0.61890638 0.69321341]	[19.78758112 16.29687283 19.99379001 15.14127961 19.77962762 13.15425825 16.9848135 15.6029566 17.31783725 14.00619945]	[3.33661856 3.11429365 3.11345334 3.2310086 3.65768234 2.87681483 3.13194066 3.18232264 3.24532016 2.68453359]"	[0.34993878 -0.4383752 -0.12809053 0.41375345 0.30813031 -0.33137309 0.63774868 -0.57701019 0.54406684 0.3592386]
Linear Regression (Backward Selection)	[0.60652707 0.53318478 0.46166591 0.69831239 0.71607606 0.66343866 0.75382306 0.62520673 0.66261871 0.74030329]	[19.85115171 13.46905069 12.25074253 13.54363397 17.01759946 12.34448867 15.00677236 14.77785622 15.3314405 11.85633277]	[3.50027812 2.8835318 2.67228715 3.009888 3.48507751 2.89419746 2.92533701 3.05664257 3.18597637 2.54312119]	[0.42420377 -0.20307851 -0.47942691 0.10475935 0.08332816 0.45694505 0.41067075 -0.75015618 0.4944253 -0.19253019]
PCA Linear Regression (All Features)	[0.41713453 0.59131602 -0.27866345 0.50613584 0.50954073 0.6181314 0.57433493	[29.40621802 11.79178629 29.09824397 22.1709983 29.39674438 14.00628097 25.94824202	[3.58294978 2.84760106 4.03789212 3.59469125 4.48768706 2.85198059 3.62423249	[0.66246406 -0.78612593 -0.53227158 0.43980954 0.56754709 0.15773222 0.66291094 -

	0.39197093 0.29011272 0.59250493]	23.97419292 32.25903439 18.60399838]	4.03197718 4.3490897 3.28072736]	1.46617341 0.57292348 0.6549504]
PCA Linear Regression (Forward Features)	[0.45058944 0.57117625 0.07263808 0.53624975 0.54374204 0.55130377 0.58465839 0.44958742 0.36288466 0.57476646]	[27.71838022 12.37288028 21.10375744 20.81909719 27.34681457 16.45740292 25.31893107 21.70241196 28.95209745 19.41384023]	[3.68050927 3.07672348 3.55509118 3.59021503 4.2569468 3.17973372 3.61727702 3.83705078 4.02411022 3.45242271]	[0.90857708 - 0.75606629 - 1.00881627 - 0.26304881 0.35525579 0.3767805 0.58307799 - 1.19075181 0.40527787 0.59896647]
PCA Linear Regression (Backward Features)	[0.4614662 0.58525835 - 0.01896447 0.49515546 0.5245098 0.59376893 0.56082378 0.4093074 0.34703107 0.53815828]	[27.16963584 11.96656865 23.18833525 22.66393946 28.49954026 14.89985421 26.77187223 23.29062719 29.67252389 21.08516947]	[3.58964359 2.93307491 3.67226978 3.81149791 4.38763699 3.02945149 3.67898751 3.78567836 4.22317644 3.39793683]	[0.64886327 - 0.59616386 - 0.77904146 - 0.34520113 0.48999953 0.21348438 0.63052415 - 1.25886876 0.54221392 0.58297266]
Ridge	[0.58410888 0.38816502 0.15216032 0.64328406 0.64791612 0.70024913 0.75341219 0.5556847 0.64881662 0.68922948]	[20.98217445 17.65331557 19.29408862 16.01401592 21.10291408 10.99434433 15.03181874 17.51906497 15.95864157 14.18808375]	[3.62433333 3.3529229 3.17470383 3.15616234 3.74629098 2.5915347 2.77011509 3.412012 3.20207032 2.86192172]	[0.24583132 - 0.53637293 0.073755 - 0.65589603 0.05659573 0.1226698 0.73892226 - 0.59077937 0.51033568 0.17272135]
Lasso	[0.57696935 0.40244748 0.08959757 0.64758382 0.6360869 0.70740588 0.75241601 0.55699173 0.64115371 0.68846592]	[21.34237207 17.24122278 20.71781436 15.82098715 21.81192394 10.73184708 15.09254518 17.46752978 16.30686323 14.22294376]	[21.34237207 17.24122278 20.71781436 15.82098715 21.81192394 10.73184708 15.09254518 17.46752978 16.30686323 14.22294376]	[3.66387311 3.33292883 3.26218721 3.13754491 3.79460998 2.51894467 2.74277207 3.36961087 3.22540441 2.88166804]" "[0.24126878 -0.50112216 0.13987391 - 0.65964624 0.00551701 0.17420509

				0.70511648 -0.4878226 0.4921955 0.12902117]
Elastic Net	[0.57677871 0.40290537 0.09895627 0.64322365 0.63617998 0.70716754 0.7538668 0.56178022 0.63980326 0.68516332]	[21.35199003 17.22801134 20.50484053 16.01672773 21.80634521 10.74058898 15.00410619 17.2787226 16.36823136 14.37372246]	[3.65786048 3.33003744 3.25031265 3.14216524 3.79661459 2.53721637 2.73349714 3.36135932 3.23022907 2.89471164]	0.23960684 -0.51822384 0.1314134 -0.67114811 0.03636513 0.15118633 0.69535517 -0.48028437 0.49630795 0.14968397]
Decision Tree	[0.68212395 0.62815628 0.64918558 0.46253485 0.77596836 0.73062609 0.91390417 0.88804049 0.30996265 0.82388659]	[16.03720395 10.7288317 7.98340145 24.12837316 13.42782429 9.88016985 5.24834079 4.41449103 31.35700452 8.04037587]	[2.27010392 1.70814188 1.91005066 2.03372735 2.40843701 2.24429932 1.4487512 1.31350474 3.79664269 1.77368461]	[-0.21358439 0.01668527 -0.4014978 -1.10637458 -0.28607894 -0.28565231 0.32465361 0.3305949 -0.95841356 -0.53226084]
Random Forest	[0.85659779 0.82848173 0.8469188 0.94523219 0.89094939 0.85720043 0.91987121 0.79940941 0.89397189 0.92846706]	[7.23480272 4.94882826 3.48363297 2.45868629 6.53618569 5.2376418 4.88459452 7.90915722 4.81817972 3.26580298]	[1.75137651 1.63524664 1.37354595 1.22241176 1.57822439 1.50087531 1.46358544 1.98431835 1.71177342 1.15520819]	[-0.01741605 -0.56704039 -0.5832352 -0.28564414 0.6393604 0.03208584 -0.46653786 -0.02167288 -0.13628708 -0.16867569]
Gradient Boosting	[0.86140632 0.88750836 0.83814373 0.92937213 0.8746886 0.84594232 0.93077346 0.8351431 0.88617126 0.91085229]	[6.99220708 3.24572892 3.68332506 3.17069055 7.51081144 5.65056974 4.22000067 6.50020113 5.17265953 4.06999753]	[1.63839191 1.48016541 1.45829331 1.38137864 1.67978864 1.54590385 1.38986203 1.93822449 1.63993335 1.33163524]	[-0.03910832 -0.52448611 -0.26379905 -0.21027241 0.69282676 0.09351131 -0.44957572 0.1423984 -0.02455045 -0.30199716]
Decision Tree (Desicion Tree	[0.89553053 0.82443091 0.46002956	[5.27060218 5.06570663 12.28798051	[1.82273774 1.60388889 2.01670921	[0.4298999 -0.07672172 -0.35641391

Feature Selection)	0.792108 0.84441876 0.68560835 0.87868043 - 0.22943503 0.73206271 0.75815572]	9.33287624 9.32510045 11.53134272 7.39555519 48.47582819 12.1757334 11.04128852]	1.66757007 1.94313564 2.04240741 1.89347479 3.80405736 1.89282922 1.92427984]	0.09135385 0.7898023 0.62081276 -0.46314043 - 1.44300026 0.30612654 - 0.42247428]
Random Forest (Desicion Tree Feature Selection)	[0.8770911 0.84067105 0.87539636 0.93504628 0.88927184 0.83198903 0.9447682 0.80428133 0.88392126 0.92439249]	[6.20089217 4.59712876 2.8355757 2.91596156 6.63673321 6.16235216 3.36689162 7.71706068 5.27490527 3.45182577]	[1.58313037 1.62503259 1.29230841 1.30943495 1.70221497 1.5263062 1.16919009 1.9851557 1.74620135 1.185002]	[0.24420066 - 0.54045259 - 0.28866628 - 0.30565114 0.69289471 - 0.0403517 -0.41585277 0.13417437 - 0.21440189 - 0.32009707]
Gradient Boosting (Desicion Tree Feature Selection)	[0.87537253 0.86662227 0.79295937 0.89685529 0.87909077 0.80430882 0.94501724 0.80710338 0.90398709 0.92435379]	[6.28759609 3.84835646 4.71157491 4.63046579 7.24695781 7.17761476 3.35171008 7.60578883 4.36306413 3.4535925]	[1.73682847 1.53765776 1.63036115 1.49644541 1.74582752 1.63846861 1.15453017 1.96915228 1.52135057 1.22484752]	[0.13434305 - 0.69726479 - 0.26110346 - 0.42436908 0.85892584 - 0.04230026 -0.40839042 0.22815188 - 0.32404649 - 0.4189111]

Appendix G: Meal Weight test-set size robustness results

Model	Test Size	R2	MAE
Gradient Boosting	0.1	0.856471	1.650582
Random Forest	0.1	0.858453	1.745295
Linear Regression	0.1	0.582337	3.675447
Gradient Boosting	0.2	0.843939	1.772495
Random Forest	0.2	0.823038	1.875613
Linear Regression	0.2	0.556089	3.337820
Gradient Boosting	0.3	0.830384	1.725027
Random Forest	0.3	0.823461	1.773778
Linear Regression	0.3	0.518821	3.300395
Gradient Boosting	0.4	0.848798	1.692075
Random Forest	0.4	0.846820	1.711581
Linear Regression	0.4	0.542919	3.274087
Gradient Boosting	0.5	0.866085	1.696754
Random Forest	0.5	0.862321	1.740300
Linear Regression	0.5	0.603425	3.308050
Gradient Boosting	0.6	0.822647	1.849324

Random Forest	0.6	0.825176	1.883345
Linear Regression	0.6	0.441306	3.836810
Gradient Boosting	0.7	0.849251	1.910078
Random Forest	0.7	0.834407	1.980172
Linear Regression	0.7	0.484199	3.770528
Gradient Boosting	0.8	0.730510	2.514780
Random Forest	0.8	0.653105	2.855348
Linear Regression	0.8	-0.681326	5.848218
Gradient Boosting	0.9	0.585752	3.144358
Random Forest	0.9	0.616788	2.947516
Linear Regression	0.9	-92.574313	31.878308

Appendix H: Meal Weight random noise robustness test

Model	Noise (+/-)	MSE	MAE
Random Forest	1.0%	7.464692	1.919919
	2.0%	7.298480	1.895949
	5.0%	6.892089	1.844348
	7.0%	6.686537	1.842619
	10.0%	6.885668	1.884450
Gradient Boosting	1.0%	6.887330	1.850132
	2.0%	5.954891	1.734328
	5.0%	6.647246	1.822525
	7.0%	7.459925	1.921764
	10.0%	6.969151	1.820474
Linear Regression	1.0%	17.804002	3.324279
	2.0%	17.997877	3.365160
	5.0%	17.666150	3.351906
	7.0%	17.376075	3.262464
	10.0%	17.623701	3.366937

Appendix I: Meal Weight models - feature importance

	Linear Regression	Linear Regression (Forward Selection)	Linear Regression (Backward Selection)	PCA Linear Regression (All Features)	PCA Linear Regression (Forward Features)	PCA Linear Regression (Backward Features)	Ridge	Lasso	Elastic Net	Decision Tree	Random Forest	Gradient Boosting
meal_volume	8.271212e-07	0.000134	0.0000001	0.685599	0.835578	0.839039	4.488227e-04	5.022015e-04	6.031411e-04	0.458683	0.203427	0.389024
meal_duration	2.443910e-09	0.0000000	0.0000000	0.0000780	0.0000000	0.0000000	2.262628e-06	2.536847e-06	3.250186e-06	0.059820	0.039459	0.072693
seconds_since_start	3.816868e-07	0.0000082	0.0000000	0.0000505	-0.0000405	0.0000000	1.263688e-04	1.451516e-04	1.838794e-04	0.003902	0.009511	0.005714
baro_press_hPa_mean	1.510578e-06	0.0000215	0.0000003	0.0076281	0.0927099	0.1047844	2.681204e-04	3.736590e-04	2.980722e-04	0.009198 1	0.008731 7	0.006611 7
rel_humidity_mean	4.485526e-09	0.0000000	0.0000000	0.0011888	0.0000000	0.0000000	8.398021e-05	1.214793e-04	1.132587e-04	0.011354	0.011809	0.014175
temp_mean_mean	1.281041e-03	0.6220800	0.0059400	0.0000071	-0.0004288	0.0016166	3.641686e-01	2.386647e-01	2.260827e-01	0.019775	0.050789	0.013096
temp_max_mean	5.376809e-04	0.0647555	0.0018089	0.0039522	0.0029100	0.0017444	2.426699e-02	2.543775e-02	2.002355e-02	0.000396	0.021079	0.035675

temp_min_mean	1.573569e-04	0.282001	0.001081	0.002096	-0.000399	0.000636	2.246631e-01	1.370005e-01	1.436618e-01	0.000364	0.025780	0.001209
temp_grass_mean (surface)	4.432794e-06	0.000471	0.000012	0.012171	0.002961	0.007573	1.338492e-03	9.909042e-04	1.173978e-03	0.000582	0.007226	0.004353
wind_dir_mean	4.117580e-07	0.000000	0.000000	0.000081	0.000000	0.000000	6.144795e-05	9.824673e-05	8.082835e-05	0.002215	0.006343	0.003116
wind_dir_gust_mean	8.287055e-07	0.000000	0.000000	-0.000367	0.000000	0.000000	2.047815e-04	4.008738e-04	3.734150e-04	0.002281	0.004924	0.021221
wind_sp_m_sec_mean	1.281846e-05	0.000000	0.000007	0.000406	0.000000	-0.000180	6.185010e-03	9.360262e-03	9.918618e-03	0.038375	0.003665	0.004847
wind_sp_m_1m_max_mean	4.698982e-06	0.000000	0.000000	0.008490	0.000000	0.000000	5.677053e-03	1.107174e-02	1.153147e-02	0.009911	0.005861	0.002950
wind_sp_m_sec_max_mean	1.820159e-06	0.000000	0.000007	0.002326	0.000000	0.004216	6.798179e-05	5.069656e-06	5.374379e-07	0.001006	0.006576	0.002600
wind_dir_std_mean	6.411883e-08	0.000028	0.000000	0.009472	0.020023	0.000000	3.246248e-08	8.079942e-07	2.864492e-11	0.010548	0.063451	0.042527
rain_mm_mean	0.000000e+00	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000
baro_press_hPa_sum	4.567787e-07	0.000000	0.000000	0.002038	0.000000	0.000000	1.302254e-02	2.484210e-02	2.674963e-02	0.060110	0.007984	0.018726
rel_humidity_sum	1.458671e-06	0.000000	0.000012	-0.000286	0.000000	0.001574	8.363805e-03	1.301426e-02	1.304573e-02	0.033711	0.007541	0.002792

temp_mean_sum	5.481406e-01	0.000000	0.494392	0.001234	0.000000	0.004323	3.725703e-03	1.269385e-02	9.996843e-03	0.000000	0.005479	0.009629
temp_max_sum	4.724712e-03	0.000000	0.000000	0.000481	0.000000	0.000000	4.708064e-03	6.041769e-05	2.384170e-04	0.000720	0.006414	0.002531
temp_min_sum	4.443688e-01	0.000000	0.495554	-0.000402	0.000000	0.004005	1.165824e-02	4.821987e-03	3.387021e-03	0.000162	0.005771	0.005053
temp_grass_sum (surface)	1.246223e-05	0.000000	0.000000	0.000067	0.000000	0.000000	7.698123e-04	1.354082e-05	8.396278e-06	0.000000	0.001062	0.009895
wind_dir_sum	4.275261e-05	0.001806	0.000000	0.000029	0.009140	0.000000	2.530233e-02	3.639840e-02	3.631339e-02	0.003504	0.006373	0.002987
wind_dir_gust_sum	4.043033e-05	0.001090	0.000000	0.001395	0.015116	0.000000	1.699148e-02	3.018478e-02	2.838204e-02	0.009623	0.005233	0.001982
wind_sp_m_sec_sum	1.920648e-04	0.000000	0.000317	-0.000607	0.000000	0.002034	1.241981e-01	2.192628e-01	2.256967e-01	0.004097	0.020713	0.003521
wind_sp_m_1m_max_sum	6.86E-06	0	0	0.001597	0	0	1.17E-02	8.56E-02	7.54E-02	0.000235	0.015551	0.012098
wind_sp_m_sec_max_sum	2.81E-04	0	0.000304	0.000002	0	0.003506	8.28E-02	5.50E-02	6.90E-02	0.008356	0.012978	0.002412
wind_dir_std_sum	6.35E-06	0.000631	0.000008	-0.003199	0.008939	0.000009	1.55E-03	2.36E-03	2.18E-03	0.000309	0.00602	0.004575
rain_mm_sum	0.00E+00	0	0	0	0	0	0.00E+00	0.00E+00	0.00E+00	0	0	0
temperature_mean	5.47E-06	0.000633	0.000004	0.014441	0.013856	0.006006	4.33E-03	5.79E-03	7.03E-03	0.00763	0.154055	0.152033

humidity_mean	8.50E-09	0	0	0.000048	0	0	2.63E-05	3.23E-05	2.95E-05	0.001396	0.019206	0.006009
pressure_mean	8.37E-08	0	0	0.043299	0	0	1.86E-04	1.92E-04	3.36E-04	0.028956	0.147875	0.06333
temperature_sum	8.04E-05	0	0.000284	0.018915	0	0.002134	3.76E-02	5.17E-02	5.32E-02	0.003202	0.007258	0.001635
humidity_sum	2.56E-07	0	0	0.011285	0	0	1.67E-03	2.36E-03	2.49E-03	0.029235	0.005154	0.004017
pressure_sum	9.16E-05	0	0.000265	-0.001336	0	0.0169	2.38E-02	3.14E-02	3.24E-02	0.004468	0.008552	0.017487

Appendix J: YOLOv8 cow detection models comparison

Model Size	Precision (B)	Recall (B)	mAP50 (B)	mAP50-95 (B)	Fitness	Preprocess Time (s)	Inference Time (ms)	Loss	Postprocess Time (s)
YOLOv8n	0.9654	0.9375	0.9321	0.6501	0.6783	2.1923	12.08	0.0	0.6923
YOLOv8s	0.9656	0.9375	0.9584	0.7340	0.7565	1.9996	16.85	0.0	0.6923
YOLOv8m	0.9666	0.9040	0.9338	0.6874	0.7120	2.0385	20.52	0.0	0.6538

Appendix J: Volume Decrease model selection results

Model	R^2	Adj R^2	MAE	MSE	RMSE
Linear Regression	0.509653	0.522066	0.023182	0.000926	0.030437
Linear Regression (Forward Selection)	0.502656	0.512201	0.023267	0.000939	0.030639
Linear Regression	0.513533	0.521389	0.022961	0.000921	0.030350

(Backward Selection)					
PCA Linear Regression (All Features)	0.454244	0.452097	0.024308	0.001036	0.032186
PCA Linear Regression (Forward Features)	0.442648	0.439932	0.024488	0.001057	0.032519
PCA Linear Regression (Backward Features)	0.454244	0.452097	0.024308	0.001036	0.032186
Ridge	0.509354	0.519025	0.023109	0.000927	0.030448
Lasso	0.510784	0.516457	0.023054	0.000925	0.030410
Elastic Net	0.510900	0.517342	0.023047	0.000924	0.030404
Decision Tree	0.910367	0.984115	0.008021	0.000171	0.013077
Random Forest	0.972856	1.000000	0.004389	0.000052	0.007221
Gradient Boosting	0.970267	0.999921	0.004945	0.000056	0.007514

Appendix K: Volume Decrease test-set size robustness results

test size	model	R2	MAE
0.1	Gradient Boosting	0.957680	0.005390
	Random Forest	0.963613	0.004620
	Linear Regression	0.397386	0.024572
0.2	Gradient Boosting	0.970699	0.004949
	Random Forest	0.962212	0.004947
	Linear Regression	0.458705	0.024501
0.3	Gradient Boosting	0.957854	0.005810
	Random Forest	0.949319	0.005642
	Linear Regression	0.477823	0.024199
0.4	Gradient Boosting	0.953115	0.006131
	Random Forest	0.939026	0.006272
	Linear Regression	0.483460	0.023220
0.5	Gradient Boosting	0.943713	0.006926
	Random Forest	0.936204	0.006879
	Linear Regression	0.490038	0.023377
0.6	Gradient Boosting	0.922225	0.008286
	Random Forest	0.916203	0.008082
	Linear Regression	0.492564	0.023226
0.7	Gradient Boosting	0.838087	0.011438
	Random Forest	0.846065	0.010923
	Linear Regression	0.472885	0.023871
0.8	Gradient Boosting	0.761978	0.014060
	Random Forest	0.778390	0.013354

	Linear Regression	0.475688	0.024373
0.9	Gradient Boosting	0.631931	0.019210
	Random Forest	0.635392	0.018392
	Linear Regression	0.389109	0.026942

Appendix L: Volume Decrease 10-fold cross validation results

Model	Mean R2	Std R2	Mean MSE	Std MSE	Mean MAE	Std MAE	Mean ME	Std ME
Linear Regression	0.509653	0.051394	0.000926	0.000165	0.023182	0.002158	-0.000015	0.003679
Linear Regression (Forward Selection)	0.502656	0.051719	0.000939	0.000163	0.023267	0.002119	-0.000014	0.003610
Linear Regression (Backward Selection)	0.513533	0.053764	0.000921	0.000178	0.022961	0.002224	-0.000045	0.003574
PCA Linear Regression (All Features)	0.454244	0.070191	0.001036	0.000213	0.024308	0.002789	-0.000033	0.004069
PCA Linear Regression (Forward Features)	0.449373	0.069442	0.001046	0.000221	0.024856	0.002891	-0.000017	0.003789
PCA Linear Regression (Backward Features)	0.452820	0.067883	0.001038	0.000211	0.024499	0.002747	-0.000010	0.004082
Ridge	0.509359	0.051879	0.000927	0.000167	0.023109	0.002129	-0.000006	0.003707
Lasso	0.510789	0.049863	0.000925	0.000166	0.023054	0.002172	-0.000023	0.003660
Elastic Net	0.510903	0.050665	0.000924	0.000166	0.023047	0.002158	-0.000027	0.003682
Decision Tree	0.910028	0.020249	0.000172	0.000052	0.008036	0.000929	-0.000319	0.001492

Random Forest	0.972949	0.009405	0.000052	0.000022	0.004376	0.000697	-0.000095	0.000761
Gradient Boosting	0.970424	0.008986	0.000056	0.000020	0.004923	0.000731	-0.000003	0.000935

Appendix M: Volume Decrease 10-fold cross validation full results

Model	R2	MSE	MAE	ME
Linear Regression	[0.39738645 0.47417116 0.52508905 0.51399482 0.48464326 0.56666132 0.52478821 0.47428098 0.57738688 0.55812556]	[0.00095746 0.00113293 0.00089265 0.00071009 0.00102713 0.00079527 0.00098815 0.001234 0.00080086 0.00072578]	[0.02457179 0.02441144 0.02340318 0.01990613 0.0246931 0.02114679 0.02385302 0.02731866 0.02194988 0.02056759]	[-0.00682161 0.00580871 -0.00296195 -0.00455452 0.00459522 0.00168186 0.0002604 0.00042844 0.00026185 0.00114775]
Linear Regression (Forward Selection)	[0.38335421 0.4642021 0.51822887 0.51202971 0.5113425 0.57634142 0.51261645 0.46719418 0.56254596 0.51870297]	[0.00097976 0.0011544 0.00090554 0.00071296 0.00097391 0.0007775 0.00101346 0.00125064 0.00082898 0.00079053]	[0.02481472 0.02497239 0.02398918 0.01986804 0.02365841 0.02047704 0.02401729 0.02713239 0.02215042 0.02158894]	[-0.00676685 0.00525632 -0.00250748 -0.00456653 0.00481483 0.00179934 -0.00027632 0.00140716 -0.0003864 0.00108187]
Linear Regression (Backward Selection)	[0.40186141 0.46321161 0.51726344 0.55208796 0.50114206 0.57594971 0.52133251 0.46869356 0.58403014 0.54975883]	[0.00095035 0.00115654 0.00090736 0.00065444 0.00099424 0.00077822 0.00099534 0.00124712 0.00078827 0.00073952]	[0.02408222 0.0244431 0.02362675 0.01895669 0.02422933 0.0209682 0.02397277 0.02699042 0.0215422 0.02079475]	[-6.76272382e-03 5.42159336e-03 -3.24016709e-03 -4.12385190e-03 4.61898793e-03 1.42870519e-03 -2.39016458e-05 5.98690643e-04 6.77765336e-04 9.57970443e-04]
PCA Linear Regression (All Features)	[0.30633916 0.39729423 0.46851187 0.56223271 0.4577143	[0.00110212 0.00129856 0.00099899 0.00063961 0.0010808	[0.0263402 0.02518747 0.02456963 0.01779087 0.02477718	[-0.00710201 0.0084925 -0.00311411 -0.0028673 0.00330336

	0.50026943 0.39949418 0.43353402 0.48809856 0.52894854]	0.00091711 0.00124869 0.00132965 0.00097006 0.0007737]	0.02312985 0.02683058 0.02828486 0.02441121 0.02175375]	0.00226421 0.00059263 0.00158141 - 0.00203498 - 0.00144245]
PCA Linear Regression (Forward Features)	[0.31004324 0.39393488 0.43732544 0.55157982 0.46860155 0.50778451 0.43226644 0.39200262 0.46380974 0.53637902]	[0.00109624 0.0013058 0.00105761 0.00065518 0.0010591 0.00090332 0.00118054 0.00142713 0.00101609 0.0007615]	[0.0264481 0.02667061 0.02557943 0.01890411 0.02489124 0.02336784 0.02652651 0.02984464 0.02492819 0.02140155]	[-0.0054827 0.00751027 - 0.00333281 - 0.00388977 0.00387427 0.00330986 - 0.00106385 0.00101165 - 0.00157142 - 0.00053107]
PCA Linear Regression (Backward Features)	[0.31082189 0.40422113 0.47520881 0.54935244 0.44645377 0.50059082 0.39478922 0.43250105 0.4776945 0.5365711]	[0.001095 0.00128364 0.0009864 0.00065843 0.00110324 0.00091652 0.00125847 0.00133207 0.00098978 0.00076118]	[0.02623442 0.02504844 0.024552 0.01854463 0.02536193 0.02310747 0.02710848 0.02865515 0.0249956 0.02138616]	[-0.00691287 0.00855757 - 0.00301897 - 0.00337445 0.00331562 0.002671 0.00055145 0.00126078 - 0.00177554 - 0.00137787]
Ridge	[0.39571806 0.4727448 0.52599554 0.51750743 0.49090814 0.57564368 0.51318583 0.4744764 0.57860562 0.5488039]	[0.00096011 0.001136 0.00089094 0.00070496 0.00101464 0.00077878 0.00101228 0.00123355 0.00079855 0.00074109]	[0.02433933 0.02430544 0.02355236 0.01971699 0.02459333 0.02079851 0.02424763 0.02691393 0.02198321 0.02064319]	[- 6.84878976e- 03 6.03869260e- 03 - 2.92776249e- 03 - 4.47416822e- 03 4.50873990e- 03 1.98152837e- 03 2.22103675e- 04 4.48385885e- 04 1.25224514e- 05 9.74798209e- 04]
Lasso	[0.39930434 0.47614183 0.52410486	[0.00095442 0.00112868 0.0008945	[0.02420316 0.02418961 0.02361447	[-0.00689554 0.00588349 - 0.0028938 -

	0.52770053 0.50220157 0.57359429 0.51073405 0.47299508 0.57416499 0.54695145]	0.00069007 0.00099213 0.00078254 0.00101738 0.00123702 0.00080697 0.00074413]	0.01940594 0.02418579 0.02086084 0.02429679 0.02710286 0.02205708 0.0206212]	0.00433232 0.00448081 0.00188086 0.00010956 0.00064996 0.00011938 0.00076335]
Elastic Net	[0.39808506 0.47566732 0.52515854 0.5247304 0.49935645 0.57508798 0.51222958 0.47412362 0.57670603 0.54788719]	[0.00095635 0.0011297 0.00089252 0.00069441 0.0009978 0.0007798 0.00101427 0.00123437 0.00080215 0.00074259]	[0.02421459 0.02421538 0.02356037 0.01952064 0.0243148 0.0207747 0.02429006 0.02700404 0.02199276 0.020583]	[- 6.92188771e- 03 5.92984784e- 03 - 2.91811980e- 03 - 4.37625762e- 03 4.48999133e- 03 1.89538526e- 03 1.15285700e- 04 5.83067716e- 04 8.30639788e- 05 8.48222324e- 04]
Decision Tree	[0.92708484 0.94489999 0.8879427 0.9252471 0.89364018 0.91861299 0.91428049 0.88744942 0.88025886 0.92085923]	[0.00011585 0.00011872 0.00021062 0.00010922 0.00021198 0.00014936 0.00017824 0.00026419 0.00022691 0.00012999]	[0.00726216 0.00706117 0.00813405 0.0072428 0.00809126 0.00803212 0.00810864 0.01012912 0.00915441 0.00714088]	[-0.00179245 - 0.00079712 - 0.00199299 0.00128102 0.00101698 0.00203681 - 0.00203683 0.00132071 - 0.00075833 - 0.00147184]
Random Forest	[0.96335465 0.97876468 0.97947548 0.97900984 0.97714243 0.98261943 0.95643973 0.96378144 0.96427319 0.98463016]	[5.82240629e- 05 4.57525963e- 05 3.85780508e- 05 3.06683396e- 05 4.55560491e- 05 3.18969901e-	[0.00464469 0.00386662 0.00398468 0.00381984 0.00435239 0.00377912 0.00523961 0.00584144 0.00469967 0.0035353]	[- 1.51968583e- 03 5.76255187e- 04 - 1.08054723e- 03 - 2.39995933e- 04 1.30531879e- 03

		05 9.05790735e-05 8.50147246e-05 6.77030403e-05 2.52449374e-05]		4.90051355e-04 - 4.72389011e-05 - 1.72822393e-04 - 1.73422901e-04 - 8.46808256e-05]
Gradient Boosting	[0.95791073 0.98000458 0.9771226 0.97346286 0.96938613 0.98301005 0.95621895 0.96366629 0.96484541 0.97861042]	[6.68736450e-05 4.30811712e-05 4.30005599e-05 3.87729362e-05 6.10146589e-05 3.11801222e-05 9.10381738e-05 8.52850324e-05 6.66186623e-05 3.51323406e-05]	[0.00532848 0.00410555 0.00479126 0.00444293 0.00552615 0.00394229 0.00575526 0.00608657 0.00521862 0.00402822]	[-0.00179098 0.00050392 - 0.00108734 - 0.00011785 0.00153917 0.000948 - 0.00058989 0.00057976 0.00024443 - 0.00025467]

Appendix N:Volume decrease random noise robustness test

Model	Noise (+/-)	MAE
Random Forest	1.0%	0.004944
	2.0%	0.005038
	5.0%	0.005074
	7.0%	0.005377
	10.0%	0.005901
Gradient Boosting	1.0%	0.005128
	2.0%	0.005479
	5.0%	0.005489
	7.0%	0.005720
	10.0%	0.005782
Linear Regression	1.0%	0.024519
	2.0%	0.024482
	5.0%	0.024741
	7.0%	0.024450

	10.0%	0.024527

Appendix O: Volume Decrease feature importance

	Linear Regression	Linear Regression (Forward Selection)	Linear Regression (Backward Selection)	PCA Linear Regression (All Features)	PCA Linear Regression (Backward Features)	PCA Linear Regression (Backward Features)	Ridge	Lasso	Elastic Net	Decision Tree	Random Forest	Gradient Boosting
hour	0.000056	0.000000	0.000115	0.054487	0.000000	0.011586	0.000369	0.000456	0.000466	0.104714	0.049305	0.033316
minutes_since_start	0.000003	0.000000	0.000000	0.000081	0.000000	0.000000	0.000255	0.000012	0.000074	0.067942	0.071150	0.067100
minutes_since_eleven	0.000137	0.066817	0.000000	0.004039	0.281467	0.000000	0.018656	0.035424	0.031244	0.031061	0.137993	0.301300
baro_press_hPa	0.000449	0.000000	0.000000	0.003028	0.000000	0.000000	0.042457	0.003019	0.012131	0.065738	0.066947	0.052726
rel_humidity	0.000624	0.000000	0.000997	0.011616	0.000000	0.000923	0.053234	0.055303	0.056291	0.037547	0.040350	0.051825
temp_mean	0.595900	0.000000	0.481369	0.025748	0.000000	0.026708	0.002982	0.000000	0.000000	0.021023	0.017555	0.010611
temp_max	0.325100	0.000000	0.506118	0.019270	0.000000	0.030713	0.014974	0.000000	0.000000	0.007510	0.014470	0.013024
temp_min	0.039833	0.000000	0.000000	0.021922	0.000000	0.000000	0.004358	0.000000	0.000000	0.033830	0.016846	0.020390
temp_grass (surface)	0.003516	0.163050	0.004518	0.014438	0.000227	0.000074	0.231575	0.307020	0.304817	0.049908	0.030451	0.028833
wind_dir	0.000052	0.009079	0.000000	0.091103	0.046752	0.000000	0.002472	0.000000	0.000240	0.012258	0.017715	0.016435

wind_dir_gust	0.000251	0.000000	0.000096	0.063317	0.000000	0.134061	0.024404	0.021434	0.021946	0.042185	0.011444	0.014935
wind_sp_m_sec	0.003013	0.000000	0.000000	0.009427	0.000000	0.000000	0.028522	0.000000	0.000000	0.006767	0.049017	0.126072
wind_sp_m_1m_max	0.002641	0.000000	0.000000	0.008984	0.000000	0.000000	0.000523	0.000000	0.000000	0.021797	0.078050	0.031882
Ws10mm	0.006442	0.446671	0.000000	0.014606	0.264644	0.000000	0.034024	0.000000	0.000000	0.035757	0.145597	0.050642
wind_sp_m_sec_max	0.019446	0.000000	0.005054	0.010323	0.000000	0.107836	0.345309	0.401906	0.391962	0.077421	0.098306	0.026277
wind_dir_std	0.000299	0.073636	0.000559	0.021931	0.043473	0.024179	0.028463	0.037199	0.035948	0.018359	0.021700	0.019365
temperature	0.000163	0.000000	0.000000	0.071303	0.000000	0.000000	0.002464	0.000000	0.000000	0.021332	0.023762	0.026474
humidity	0.000662	0.209578	0.000788	0.519306	0.346617	0.610798	0.043196	0.089437	0.072261	0.293625	0.042322	0.030484
pressure	0.001414	0.031170	0.000387	0.035071	0.016819	0.048839	0.118513	0.044675	0.068421	0.051224	0.068020	0.078309

Appendix P: Weight Decrease model selection results

Model	R^2	Adj R^2	MAE	MSE	RMSE	ME
Linear Regression	0.421820	0.431389	0.013157	0.000355	0.018851	-1.568047e-17
Linear Regression (Forward Selection)	0.406938	0.413695	0.013598	0.000365	0.019105	1.030104e-18
Linear Regression (Backward Selection)	0.425546	0.432292	0.013156	0.000353	0.018785	-1.648166e-17
PCA Linear Regression (All Features)	0.251695	0.244839	0.014899	0.000461	0.021462	2.117436e-18
PCA Linear Regression	0.251695	0.244839	0.014899	0.000461	0.021462	1.774068e-18

(Forward Features)						
PCA Linear Regression (Backward Features)	0.251695	0.244839	0.014899	0.000461	0.021462	6.867359e-19
Ridge	0.422156	0.430924	0.013157	0.000355	0.018849	-1.156005e-17
Lasso	0.415950	0.422561	0.013333	0.000359	0.018960	-3.319223e-18
Elastic Net	0.416796	0.423452	0.013314	0.000359	0.018946	-3.891503e-18
Decision Tree	0.883456	0.999997	0.003754	0.000069	0.008327	2.682562e-21
Random Forest	0.973903	1.000000	0.002008	0.000016	0.003948	3.665184e-18
Gradient Boosting	0.974076	0.999997	0.002108	0.000016	0.003944	-2.770304e-19

Appendix Q: Weight Decrease test-set size robustness results

test size	model	R2	mae
0.1	Gradient Boosting	0.968874	0.002172
	Random Forest	0.950726	0.002644
	Linear Regression	0.465542	0.012219
0.2	Gradient Boosting	0.971859	0.002153
	Random Forest	0.963575	0.002328
	Linear Regression	0.445478	0.013304
0.3	Gradient Boosting	0.964329	0.002539
	Random Forest	0.953619	0.002690
	Linear Regression	0.403196	0.013579
0.4	Gradient Boosting	0.954253	0.002704
	Random Forest	0.941499	0.002977
	Linear Regression	0.388373	0.013470
0.5	Gradient Boosting	0.942128	0.003282
	Random Forest	0.947244	0.003075
	Linear Regression	0.412763	0.013522
0.6	Gradient Boosting	0.929164	0.003626
	Random Forest	0.926233	0.003556
	Linear Regression	0.417712	0.013554
0.7	Gradient Boosting	0.836322	0.004943
	Random Forest	0.847587	0.004716
	Linear Regression	0.378315	0.014269
0.8	Gradient Boosting	0.799671	0.005986
	Random Forest	0.826615	0.005602
	Linear Regression	0.369281	0.014674
0.9	Gradient Boosting	0.700689	0.007956
	Random Forest	0.714747	0.007762

	Linear Regression	0.204681	0.016906

Appendix R: Weight Decrease 10-fold cross validation results

Model	Mean R2	Std R2	Mean MSE	Std MSE	Mean MAE	Std MAE	Mean ME	Std ME
Linear Regression	0.421820	0.075140	0.000355	0.000070	0.013157	0.001239	-0.000052	0.001345
Linear Regression (Forward Selection)	0.406938	0.073340	0.000365	0.000074	0.013598	0.001170	-0.000032	0.001494
Linear Regression (Backward Selection)	0.425546	0.069474	0.000353	0.000067	0.013156	0.001183	-0.000035	0.001314
PCA Linear Regression (All Features)	0.251695	0.032792	0.000461	0.000071	0.014899	0.001010	-0.000020	0.001502
PCA Linear Regression (Forward Features)	0.282410	0.050380	0.000441	0.000072	0.014983	0.001073	-0.000006	0.001252
PCA Linear Regression (Backward Features)	0.282004	0.051591	0.000441	0.000072	0.014996	0.001063	-0.000011	0.001264
Ridge	0.422156	0.074766	0.000355	0.000071	0.013157	0.001256	-0.000053	0.001349
Lasso	0.415950	0.074663	0.000359	0.000074	0.013333	0.001246	-0.000054	0.001398
Elastic Net	0.416796	0.074745	0.000359	0.000074	0.013314	0.001248	-0.000054	0.001394
Decision Tree	0.886309	0.052781	0.000068	0.000028	0.003727	0.000811	0.000016	0.000847
Random Forest	0.973701	0.011172	0.000016	0.000006	0.002007	0.000364	0.000057	0.000397

Gradient Boosting	0.974580	0.008637	0.000015	0.000005	0.002072	0.000336	0.000175	0.000405

Appendix S: Weight Decrease 10-fold cross validation full results

Model	R2	MSE	MAE	ME
Linear Regression	[0.46554221 0.43495178 0.30695705 0.34464005 0.48385545 0.49221553 0.50542305 0.30517883 0.49064552 0.38878992]	[0.00031718 0.00039697 0.00035113 0.000321 0.00034372 0.00028763 0.00030071 0.00053261 0.00029676 0.00040579]	[0.01221928 0.01400711 0.01375082 0.01241554 0.01363851 0.01170488 0.01260647 0.01615113 0.01205704 0.01301705]	[-0.00055453 0.00042165 -0.002236 -0.00163441 0.0006788 -0.00033343 0.00102634 -0.00077371 0.00010186 0.00278106]
Linear Regression (Forward Selection)	[0.46262656 0.39639461 0.30394939 0.33923327 0.45908146 0.45670915 0.49883164 0.28375992 0.48471086 0.38408505]	[0.00031891 0.00042406 0.00035265 0.00032365 0.00036022 0.00030775 0.00030472 0.00054903 0.00030022 0.00040891]	[0.01288184 0.01424176 0.01387598 0.01289787 0.01411423 0.01259458 0.01291742 0.01663299 0.01252902 0.0132915]	[-0.00029073 0.00051867 -0.00220517 -0.00193906 0.00048127 -0.00011785 0.00069363 -0.00119292 0.0004085 0.0033213]
Linear Regression (Backward Selection)	[0.45632648 0.44475632 0.32621335 0.34876799 0.4990439 0.48693678 0.50479605 0.3163152 0.47845776 0.39384412]	[0.00032265 0.00039008 0.00034137 0.00031898 0.00033361 0.00029062 0.00030109 0.00052408 0.00030386 0.00040244]	[0.01235948 0.0139617 0.01351992 0.01240267 0.01342902 0.01173924 0.01270583 0.01614135 0.01225406 0.01304628]	[-0.00054331 0.00050365 -0.00200777 -0.0016777 0.0007887 -0.00028588 0.00095237 -0.0007346 -0.0001274 0.00277838]
PCA Linear Regression (All Features)	[0.27129421 0.26802003 0.19224393 0.2790808 0.25391239 0.27711223 0.28980892 0.19152746 0.25197668 0.24197605]	[0.00043246 0.00051425 0.00040924 0.00035311 0.00049685 0.00040948 0.00043181 0.00061973 0.00043582 0.00050326]	[0.01451108 0.0145826 0.01469161 0.01341237 0.01579058 0.01387224 0.0150935 0.01730066 0.01474598 0.01499362]	[-3.40214987e-04 2.94597383e-03 -2.57624322e-03 -1.68585813e-03 4.83499035e-04 8.81569528e-05 1.29648609e-03 -2.26533638e-04 -1.16347944e-03

				9.82949076e-04]
PCA Linear Regression (Forward Features)	[0.31692603 0.31490094 0.20011486 0.26647176 0.32464033 0.29925996 0.34310367 0.18960962 0.31400014 0.25507211]	[0.00040538 0.00048131 0.00040526 0.00035928 0.00044975 0.00039693 0.0003994 0.0006212 0.00039968 0.00049457]	[0.01429332 0.01515816 0.01457066 0.01384898 0.01518032 0.01450118 0.01520794 0.01792867 0.0142492 0.01489442]	[-0.00055805 0.00214638 - 0.00181014 - 0.00166103 0.00100614 - 0.00021659 0.00093199 - 0.00076141 - 0.0005245 0.00139129]
PCA Linear Regression (Backward Features)	[0.31576063 0.3200193 0.20120074 0.2632932 0.33323925 0.29851816 0.34475291 0.18605396 0.3019196 0.25528637]	[0.00040607 0.00047772 0.00040471 0.00036084 0.00044402 0.00039735 0.0003984 0.00062393 0.00040672 0.00049443]	[0.01433637 0.01515994 0.01448158 0.01383341 0.0149799 0.01454035 0.01530172 0.01794332 0.014551 0.01482917]	[-0.00073153 0.00205018 - 0.00167028 - 0.00173365 0.00115151 - 0.00023136 0.00083359 - 0.0007285 - 0.00061901 0.00156415]
Ridge	[0.46671349 0.43072657 0.31245214 0.34599882 0.48363847 0.48784057 0.50876126 0.30280788 0.49342814 0.38919128]	[0.00031649 0.00039994 0.00034834 0.00032033 0.00034387 0.00029011 0.00029868 0.00053443 0.00029514 0.00040552]	[0.01223334 0.01405783 0.01371908 0.01241015 0.01367297 0.0117325 0.01259448 0.01619235 0.0119814 0.01297782]	[-0.00046966 0.00035976 - 0.00221743 - 0.00165808 0.00062671 - 0.00030534 0.00093078 - 0.00081859 0.00016638 0.0028569]
Lasso	[0.46574229 0.40863476 0.31657275 0.34542338 0.47422405 0.46747835 0.51324576 0.29049737 0.49388443 0.38380177]	[0.00031706 0.00041546 0.00034625 0.00032061 0.00035013 0.00030165 0.00029595 0.00054387 0.00029488 0.0004091]	[0.01252009 0.01430434 0.01369424 0.01252166 0.01384999 0.01215526 0.0126936 0.01640519 0.01207845 0.01310899]	[-0.00027064 0.00017766 - 0.0021703 - 0.00176329 0.00049582 - 0.0002332 0.00072107 - 0.00096609 0.00034044 0.00312683]
Elastic Net	[0.46620169 0.41047526 0.31671011 0.34575336 0.47536897 0.46925004 0.51386824 0.29160902 0.49425743 0.38446914]	[0.00031679 0.00041417 0.00034618 0.00032045 0.00034937 0.00030064 0.00029557 0.00054301 0.00029466 0.00040866]	[0.01249605 0.01428557 0.01369535 0.01251051 0.01383004 0.01211356 0.01267776 0.0163864 0.01205766 0.01308946]	[-0.00028433 0.00018935 - 0.0021739 - 0.00175545 0.00050499 - 0.00023812 0.00073473 - 0.00095721 0.00032983 0.00310708]

Decision Tree	[0.92540407 0.96704939 0.82125922 0.88394143 0.88452432 0.86867357 0.87269132 0.90337651 0.78406828 0.95210683]	[4.42701145e-05 2.31492705e-05 9.05577169e-05 5.68458817e-05 7.68997296e-05 7.43899114e-05 7.74053052e-05 7.40662425e-05 1.25807759e-04 3.17969394e-05]	[0.00305044 0.00252937 0.00394289 0.00293845 0.00453588 0.00383559 0.00465646 0.00374702 0.00509538 0.00294007]	[-6.63413124e-05 - 5.14934127e-04 - 3.81915857e-04 - 1.40637838e-03 - 4.79789253e-04 1.59722958e-03 1.53278338e-04 1.33510996e-03 2.79231712e-04 - 3.51836980e-04]
Random Forest	[0.94995923 0.98757003 0.96073409 0.97561332 0.97108812 0.97885888 0.96679967 0.98406387 0.97796223 0.98436081]	[2.96974701e-05 8.73260437e-06 1.98937879e-05 1.19446810e-05 1.92535416e-05 1.19753951e-05 2.01862236e-05 1.22157619e-05 1.28398125e-05 1.03830784e-05]	[0.00265262 0.00149703 0.00248361 0.00165789 0.00225982 0.00179472 0.0021898 0.00173538 0.00207093 0.00172766]	[-3.19979751e-04 - 4.06255324e-05 - 5.94721594e-04 2.57455107e-05 4.39476385e-04 4.57421562e-04 - 5.48462535e-04 3.81818734e-04 3.13247085e-04 4.54099689e-04]
Gradient Boosting	[0.96676807 0.98677799 0.96579356 0.97948475 0.97105331 0.97731777 0.9606888 0.98593297 0.96931708 0.98266582]	[1.97220055e-05 9.28905035e-06 1.73304440e-05 1.00484398e-05 1.92767244e-05 1.28483567e-05 2.39017118e-05	[0.00216349 0.00167503 0.00241313 0.00169593 0.00247576 0.00195616 0.00254589 0.00173576 0.00233671 0.00172672]	[0.00018355 0.00011369 - 0.00062491 0.00023678 0.0003203 0.00057483 - 0.00045423 0.0001478 0.00054815 0.00069914]

		1.07830064e-05 1.78767157e-05 1.15084045e-05]		

Appendix T: Weight decrease random noise robustness test

Model	Noise (+/-)	MAE
Random Forest	1.0%	0.002403
	2.0%	0.002345
	5.0%	0.002391
	7.0%	0.002620
	10.0%	0.002638
Gradient Boosting	1.0%	0.002227
	2.0%	0.002162
	5.0%	0.002471
	7.0%	0.002415
	10.0%	0.002539
Linear Regression	1.0%	0.013308
	2.0%	0.013298
	5.0%	0.013325
	7.0%	0.013194
	10.0%	0.013470

Appendix U: Weight Decrease feature importance

	Linear Regression	Linear Regression	Linear Regression	PCA Linear Regression	PCA Linear Regression	PCA Linear Regression	Ridge	Lasso	Elastic Net	Decision Tree	Random Forest	Gradient Boosting
hour	0.000091	0.007344	0.000080	-0.005779	0.017419	0.026358	0.000127	0.000760	0.000627	0.002631	0.070117	0.071107
minutes_since_start	0.000149	0.009583	0.000177	0.012661	0.032734	0.045320	0.000196	0.000932	0.000782	0.060384	0.022165	0.040387
minutes_since_eleven	0.001693	0.165173	0.001387	0.009497	0.031024	0.034009	0.002350	0.013922	0.011499	0.157637	0.212356	0.249550
baro_press_hPa	0.000231	0.017038	0.000094	0.033816	0.053520	0.011121	0.000395	0.003774	0.003040	0.032627	0.014260	0.013064
rel_humidity	0.000254	0.087656	0.000000	-0.013678	0.004879	0.000000	0.000414	0.004090	0.003265	0.005180	0.103939	0.098944
temp_mean	0.040765	0.000000	0.000000	0.000310	0.000000	0.000000	0.010075	0.000000	0.000000	0.002998	0.011320	0.022121
temp_max	0.367020	0.000000	0.540270	0.001632	0.000000	0.000511	0.451575	0.511648	0.515604	0.003245	0.011547	0.012239

temp_min	0.583395	0.000000	0.450467	0.002883	0.000000	0.002725	0.526782	0.422614	0.430259	0.003856	0.008200	0.003934
temp_grass	0.003301	0.218095	0.003415	0.004388	0.013568	0.027081	0.004400	0.021659	0.018018	0.232414	0.248707	0.251636
wind_dir	0.000188	0.001663	0.000110	0.258827	0.630569	0.588617	0.000249	0.001259	0.001056	0.153510	0.122862	0.055335
wind_dir_gust	0.000003	0.000000	0.000000	0.265790	0.000000	0.000000	0.000007	0.000164	0.000127	0.008081	0.009833	0.015758
wind_sp_m_sec	0.000406	0.000000	0.000000	0.038384	0.000000	0.000000	0.000374	0.000000	0.000000	0.157029	0.025591	0.031002
wind_sp_m_1m_max	0.000587	0.453457	0.000000	0.073132	0.064128	0.000000	0.000690	0.002991	0.002481	0.003280	0.029460	0.025769
Ws10mm	0.000603	0.000000	0.002293	0.115426	0.000000	0.067876	0.000849	0.005085	0.004567	0.017311	0.033263	0.011175
wind_sp_m_sec_max	0.000324	0.000000	0.000000	0.078152	0.000000	0.000000	0.000148	0.002588	0.001722	0.006471	0.013418	0.008806
wind_dir_std	0.000229	0.030791	0.000157	0.029636	0.007596	0.002261	0.000331	0.002300	0.001865	0.002114	0.003445	0.004011
temperature	0.000351	0.000000	0.000743	0.006442	0.000000	0.057144	0.000448	0.002234	0.001841	0.044861	0.030475	0.036722
humidity	0.000396	0.009200	0.000806	0.036864	0.144563	0.136975	0.000552	0.003449	0.002820	0.036275	0.014257	0.016889
pressure	0.000014	0.000000	0.000000	0.051617	0.000000	0.000000	0.000037	0.000532	0.000427	0.000096	0.014786	0.031550

Data availability statement

Data and code available in the link: https://github.com/benjika/research_code

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